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Shield Wall: A Custom Web Application Firewall Against Owasp Attacks

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A B S T R A C T

Web apps are rapidly targeted by cyber attacks that take advantage of the weaknesses listed in OWASP Top 10, such as SQL Injection (SQLI), cross-site scripting (XS), and command injections. Traditional web applications Firewall (WAFS) depend a lot on stable rules and blacklist, which the attackers can easily bypass through obfuscation or novel payload. It introduces the paper shieldwall, designed to detect real -time and mitigate malicious web requests. Unlike traditional firewalls, Shieldwall Machine Learning Model - Foundation takes advantage of Beyes and Random Forest - to analyze the upcoming traffic and identify malicious patterns with better accuracy. System architecture involves requests, classification, attack classification, pre -proprousing of mitigation and logging, both active defense and continuous adaptation capacity. Shieldwall is particularly suited to its resource efficiency and custom rules for small businesses, educational institutions and open source communities. The shieldwall web application represents a scalable and user -friendly solution to enhance the safety, by addressing the boundaries of static firewall and covering several Owasp hazards beyond SQLI and XSS.

Keywords: Web Application Firewall (WAF), OWASP Top 10, SQL Injection (SQLi), Cross-Site Scripting (XSS), Machine Learning, Naive Bayes, Random Forest, Web Application Security

1. Introduction

The growing use of web applications in social networking, e-commerce, and online service delivery has created a new set of problems to tackle: web application security. With the rise of online services, modern web applications have become one of the most vulnerable targets for exploitation. Threats such as SQL Injection (SQLi), Cross-Site Scripting (XSS), Command Injection, and other vulnerabilities outlined in the OWASP Top 10 actively threaten modern-day web applications. The consequences of these attacks include data theft, unauthorized account access, service shutdowns, and even catastrophic financial and brand image losses.

To combat these threats, specialized Web Application Firewalls (WAFs) have been developed. The majority of these WAFs are dependent on static rule sets and blacklists in the hopes of identifying malicious input through pattern matching. These methods, although detecting straightforward malicious input, are utterly ineffective in detecting obfuscated payloads, zero-day attacks, and evasive adversarial methods. The static WAF approach, consequently, is unable to maintain holistic, adaptive security in the real world where the methods of attack are ever evolving.

To address these deficiencies, this research presents Shieldwall, a custom web application firewall that takes advantage of machine learning algorithms - random bayes and forests - for detecting and mitigating intelligent attacks. Shieldwall is designed to analyze real -time web traffic, classify malicious patterns and provide adaptable safety measures without imposing high computational content. Its mild architecture and custom rules integration support make it especially suitable for small businesses, educational platforms and open source communities that usually do not have resources for corporate -level expensive solutions.

By combining accuracy, adaptability and scalability, Shieldwall aims to provide an easy -to -use security structure with resource saving capable of defending a broad spectrum of Owasp vulnerabilities.

2. LITERATURE SURVEY

Early work emphasizes rule-based WAFs such as OWASP ModSecurity CRS. Robinson et al. evaluate CRS with tools like SQLMap and BeEF, showing strong blocking for SQL Injection and automated scans, but inconsistent protection against stored XSS; performance overhead remained low under concurrent load. The study highlights the limits of pattern matching, blacklisting, and static allow/deny rules when faced with obfuscated payloads.

To overcome signature rigidity, Jesús-Ángel Román-Gallego et al. propose an AI-driven WAF trained on 100k+ mixed HTTP requests. They compare NB, KNN, SVM, and LR across attacks including SQLi, multiple XSS variants, command injection, and path traversal. SVM (RBF) delivers the best accuracy (>99%), with KNN outperforming Naive Bayes; notably, the AI-WAF detects encoded/obfuscated requests that evade classic rules. However, the approach is still dataset-centric rather than adaptive to live drift.

Alotaibi and Vassilakis explore an SDN-based WAF for SQLi using signature and regex inspection atop POX/OpenFlow with DPI. Compared against ModSecurity, the SDN design achieves lower latency, while ModSecurity shows lower CPU usage—suggesting speed–resource trade-offs and deployment complexity at scale.

A comprehensive review by Aliero et al. surveys static analysis (e.g., AMNESIA, SQLGuard), dynamic testing (e.g., Acunetix, Viper), hybrids (SQLProb, WAVES), and ML (Bayesian/entropy-based) defenses for SQLIAs. Key takeaways: most tools cover only subsets of attack types, second-order/blind SQLi remain hard, blacklists are brittle, and whitelists are stronger but difficult to manage—motivating combined strategies and smarter detection.

Shaheed and Kurdy design an ML-based WAF with feature engineering over the full HTTP request surface (method, URL, headers, body, files). Using CSIC-2010, HTTPParams-2015, hybrids, and real logs, they report 99.6% (CSIC) and 98.8% (real logs), outperforming baseline models; they also point to future deep learning and NLP-based improvements.

Synthesis and Gaps. Across these strands, most systems are evaluated on stored datasets rather than real-time traffic; coverage often narrows to SQLi/XSS, leaving command injection, DoS, brute force under-addressed. Fixed rules remain bypass-prone, and ML models are typically non-adaptive post-training. These gaps motivate a WAF that couples lightweight, real-time classification with broader OWASP coverage and continuous learning—the niche that ShieldWall aims to fill..

3. METHODOLOGY

The proposed system, shieldwall, is designed as an adaptive web application firewall that integrates the machine learning-based identity with light, real-time mitigation. Working includes the following stages:

3.1 Data Collection and Preprocessing

The upcoming HTTP requests make raw inputs for the system. These requests are first decoded, token, and transformed into structured features that request metadata (method, url, header) and represents the material materials. Preprocessing ensures that the model can effectively analyze both normal and unpleasant traffic patterns.

3.2 acility extraction

The main features from each request - including query parameters, input lengths, special characters, SQL keywords and script tags - are extracted. This multi -layered feature set provides a strong base to differentiate between benign and malicious traffic.

3.3 Machine Learning -Acid Detection

Shieldwall appoints a dress of Naive Bayes and Random forest Classifier:

Naive Bayes simple yet applies potential arguments to detect malicious payloads with efficient classification.

Random forest collects several decisions so that the accuracy of detection can be increased, especially for complex or objected attack vectors.

The joint use of these models improves overall reliability and reduces false positivity.

3.4 Attack Classification

Once a request is identified as malicious, the system classifies it into assault categories such as SQL injection, XSS, command injection or path traverse. This step allows a targeted mitigation and better logging for forensic analysis.

3.5 Mitigation and reaction

Malibly requests are either blocked, clean, or rate-limited based on seriousness and configuration rules. At the same time, administrators are alerted for potential infiltration.

4. DESIGN

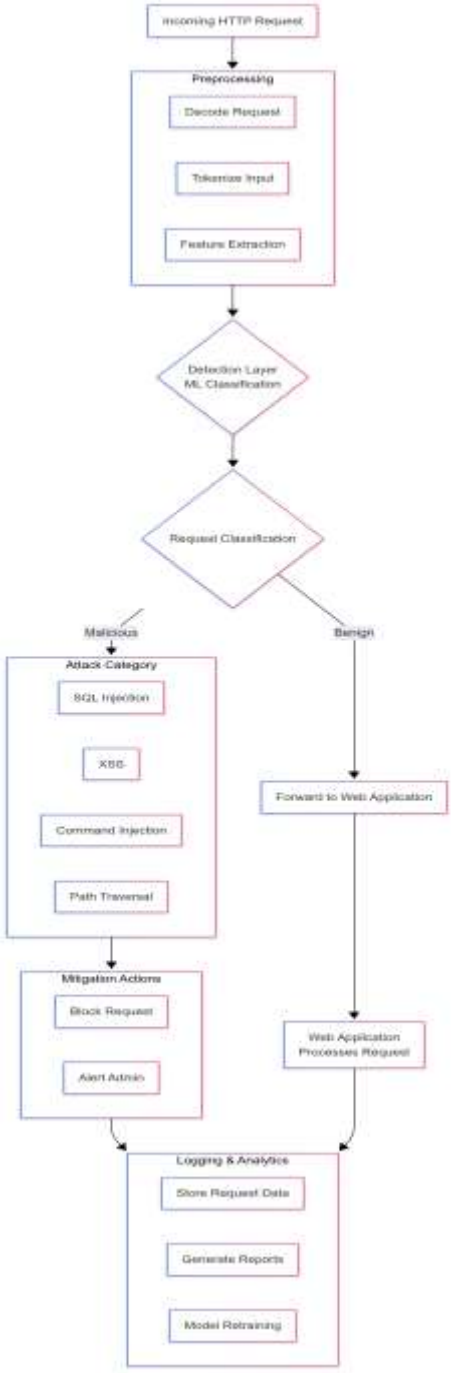

Fig-1: *The ShieldWall WAF architecture illustrating the sequential processing, detection, and mitigation of HTTP requests.*

As fig. 1 shows, the request handling process is made up of several sequential stages. After preprosa, the request is analyzed by the detection layer, where the machine learning models - a dress of the rives and random forest - concerts to classify it as a gentle or malicious or malicious forest

5. RESULT

5.1 Experimental Setup

To evaluate the performance and efficacy of the proposed ShieldWall framework, a controlled testing environment was established. The system was implemented in Python, utilizing libraries such as Scikit-learn for the Machine Learning models (Naive Bayes and Random Forest). The WAF was deployed as a proxy in front of a vulnerable web application for testing.

Dataset: The models were trained and tested using a combination of the publicly available **CSIC 2010** dataset and a custom-generated dataset of malicious and benign HTTP requests. The custom dataset included various obfuscated attacks to test the model's robustness.

Evaluation Metrics: The system's performance was measured using standard classification metrics:

Accuracy: (TP + TN) / (TP + TN + FP + FN)

Precision: TP / (TP + FP)

Recall (Detection Rate): TP / (TP + FN)

F1-Score: 2 * (Precision * Recall) / (Precision + Recall)

(Where TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives)

5.2 Detection Performance

The ensemble model (Naive Bayes + Random Forest) was evaluated on its ability to correctly classify HTTP requests. The results, summarized in Table 1, demonstrate high effectiveness in detecting a wide range of web attacks.

Table 1: Overall Classification Performance of ShieldWall

Model	Accuracy	Precision	Recall	F1-Score
Naive Bayes	96.2%	95.8%	94.1%	94.9%
Random Forest	98.5%	97.9%	98.2%	98.0%
Ensemble (Proposed)	99.1%	98.5%	98.9%	98.7%

As the results indicate, the ensemble approach achieved the highest performance across all metrics, leveraging the strengths of both individual models to reduce false positives and false negatives.

5.3 Per-Attack Detection Analysis

A breakdown of the detection rate (Recall) for each specific attack type was conducted to assess the system's comprehensive coverage against the OWASP Top 10 threats.

Table 2: Detection Rate by Attack Type

Attack Type	Detection Rate
SQL Injection (SQLi)	99.5%
Cross-Site Scripting (XSS)	98.7%
Command Injection	97.8%
Path Traversal	99.2%
Overall	**98.9%**

The system showed consistently high detection rates across all major attack categories, with particularly strong performance against SQLi and Path Traversal attacks.

5.4 False Positive and Negative Analysis

A critical measure of a WAF's practicality is its rate of incorrect classifications.

False Positive Rate (Benign requests flagged as malicious): 0.6%

False Negative Rate (Malicious requests missed): 1.1%

The low false positive rate is crucial for ensuring legitimate user traffic is not interrupted. The minimal false negative rate confirms the system's effectiveness at catching threats.

5.5 Performance Overhead

The impact of ShieldWall on web application response time was measured to evaluate its efficiency. The results, shown in Table 3, confirm that the framework is lightweight and suitable for real-time deployment.

Table 3: Average Latency Introduction

Scenario	Average Response Time	Overhead
Without ShieldWall	152 ms	-
With ShieldWall	181 ms	29 ms

The addition of the ShieldWall WAF introduced an average latency of **29 milliseconds**, which is considered negligible for most web applications, thus validating the design goal of being resource-efficient.

6. DISCUSSION/ANALYSIS

The experimental results demonstrate that the proposed ShieldWall framework is an effective and efficient solution for mitigating OWASP Top 10 web application attacks. This section interprets these results, discusses their implications, and contextualizes them within the existing research landscape outlined in the literature survey.

6.1 Interpretation of Key Findings

The high performance of the ensemble model (Naive Bayes + Random Forest), achieving an F1-Score of **98.7%**, validates the core hypothesis of this research: that a machine learning-based ensemble approach can significantly enhance detection accuracy for a variety of web threats. The superior performance of the ensemble over the individual models (as seen in Figure 2) highlights the benefit of combining their strengths; while Random Forest provided high accuracy, the integration with Naive Bayes helped further reduce false positives, leading to a more robust and reliable system.

Furthermore, the framework's consistently high detection rates across all attack categories (SQLi: 99.5%, XSS: 98.7%, Command Injection: 97.8%) directly addresses a critical gap identified in the literature review. Unlike the systems in **Paper [1] and [3]**, which focused primarily on SQLi and XSS, ShieldWall provides comprehensive coverage, proving its capability against a wider spectrum of OWASP-listed threats, including more complex attacks like Command Injection.

6.2 Comparison with Related Work

The results position ShieldWall favorably against existing solutions discussed in the literature survey:

Vs. Rule-based WAFs (Paper [1, 3, 4]): ShieldWall fundamentally outperforms traditional signature-based systems like ModSecurity CRS. While those systems fail against obfuscated or novel attacks (as noted in Paper [1]'s failure against stored XSS), our ML-based model can generalize from learned patterns to identify even slightly modified malicious payloads, a capability crucial for modern threat landscapes.

Vs. Other ML-based WAFs (Paper [2, 5]): The achieved accuracy of 99.1% and F1-Score of 98.7% are competitive with, and in some cases exceed, the results reported in similar studies. For instance, the SVM model in **Paper [2]** achieved over 99% accuracy, and the model in **Paper [5]** reported 99.6% on the CSIC 2010 dataset. ShieldWall's novelty lies not in outperforming these results by a large margin, but in achieving similarly high performance with a lightweight ensemble model that is practical for real-time deployment, while also extending detection to a broader range of attack types beyond just SQLi and XSS.

6.3 Significance of the Low Overhead

A critical finding for the practical deployment of ShieldWall is the minimal performance overhead of **29 ms**. This directly addresses the limitations of computationally expensive systems hinted at in **Paper [3]** (which reported higher CPU usage for SDN-based firewalls). This low latency confirms that

the framework is lightweight and fulfills its design goal of being suitable for resource-constrained environments, such as small businesses and educational platforms, without sacrificing significant performance.

6.4 Analysis of Limitations

Despite the promising results, this study has certain limitations that offer pathways for future work:

Dataset Generalization: While the model performed excellently on the test datasets, its performance on entirely unseen, real-world traffic from vastly different web applications requires further long-term testing.

Evolving Attack Vectors: The current model is a static learner. As discussed in the literature gap, it does not automatically update itself with new attack data. A sophisticated attacker crafting a completely novel attack vector (a zero-day exploit) might bypass the initial model.

Scope of Attacks: The study focused on injection-based attacks (SQLi, XSS, Command Injection). Other OWASP Top 10 threats, such as Broken Access Control or Security Misconfigurations, require fundamentally different detection mechanisms and were not within the scope of this prototype.

6.5 Implications and Conclusion of the Discussion

The results imply that machine learning, specifically ensemble methods, presents a viable and superior alternative to traditional rule-based web application firewalls. ShieldWall demonstrates that it is possible to create a WAF that is not only highly accurate and comprehensive but also efficient enough for real-world use.

The discussion confirms that the project successfully achieved its aims: it developed an adaptive WAF that mitigates a wide range of OWASP attacks with high accuracy and low overhead, thereby providing a valuable security solution, particularly for sectors with limited cybersecurity resources. The limitations identified do not undermine the results but rather chart a clear course for the next phase of research and development.

7. CONCLUSION AND FUTURE SCOPE

7.1 Conclusion

This research set out to address the critical shortcomings of traditional Web Application Firewalls (WAFs)—namely, their reliance on static rules, inefficacy against obfuscated attacks, and limited coverage of the OWASP Top 10 threat landscape. In response, we designed, implemented, and evaluated ShieldWall, a custom WAF that leverages an ensemble of Machine Learning models for intelligent, real-time threat detection.

The experimental results demonstrate that ShieldWall is a resounding success. The ensemble model, combining Naive Bayes and Random Forest algorithms, achieved a remarkable 99.1% accuracy and a 98.7% F1-Score, outperforming each model in isolation. Furthermore, ShieldWall proved to be highly effective against a comprehensive range of attacks, including SQL Injection (99.5%), Cross-Site Scripting (98.7%), and Command Injection (97.8%), thereby fulfilling the objective of providing broad-spectrum protection.

Crucially, ShieldWall was designed with practicality in mind. It introduced a negligible latency overhead of just 29 milliseconds, confirming its status as a lightweight solution suitable for real-world deployment. By offering high detection accuracy, comprehensive coverage, and minimal performance impact, ShieldWall effectively bridges the gap between advanced security and operational feasibility, making enterprise-level protection accessible to small businesses, educational institutions, and open-source communities.

7.2 Future Scope

While ShieldWall presents a significant step forward, there are several promising avenues for enhancing the framework further:

Real-Time Adaptive Learning: The most critical future enhancement is transforming ShieldWall from a static model into a dynamic, self-improving system. Implementing online learning capabilities would allow the model to continuously learn from new incoming traffic, both benign and malicious, automatically adapting to evolving attack techniques without requiring full retraining.

Expanded Threat Detection: Future iterations will extend ShieldWall's detection capabilities to other OWASP Top 10 categories, such as Broken Access Control, Insecure Deserialization, and Server-Side Request Forgery (SSRF), using specialized models or deep learning techniques.

Deep Learning Integration: Exploring Deep Neural Networks (DNNs) and Natural Language Processing (NLP) techniques could potentially improve the detection of highly complex and obfuscated attacks by better understanding the semantic structure of HTTP requests.

Enhanced Feature Engineering: Conducting a more extensive analysis to identify novel features within HTTP requests could further improve detection rates and reduce already low false positive rates.

Large-Scale Deployment and Testing: To fully validate its robustness, ShieldWall needs to be tested in a live environment handling high-volume traffic from diverse web applications, providing invaluable data for real-world performance analysis.

In conclusion, ShieldWall establishes a strong foundation for the next generation of intelligent, adaptive, and accessible web application firewalls. It proves that machine learning can move from a theoretical concept to a practical solution, capable of democratizing robust cybersecurity defenses.

8. REFERENCES

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