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Reverse Proxy-Based SQL Injection Prevention via Real-Time SQL Query Monitoring and Sanitization

[1] Mantri Sowmya, [2] Power Naveen, [3] Golkonda Pranay, [4] Tungala Neeraj, [5] Boojala Sourya
[6] P.Likhith, [7] Mrs.K.Priyanka

[1,2,3,4,5] UG scholar,Dept. of CSE, Narasimha Reddy College Of Engineering, Maisammaguda, Kompally,Hyderabad, Telangana

[6] UG scholar,Dept. of EEE, Narasimha Reddy College Of Engineering, Maisammaguda, Kompally,Hyderabad, Telangana

[7] Assistant Professor, Dept. of CSE, Narasimha Reddy College Of Engineering, Maisammaguda, Kompally,Hyderabad, Telangana

Abstract

SQL injection (SQLi) attacks remain a prevalent threat to web applications, compromising database integrity and exposing sensitive data. This study proposes a reverse proxy-based system for SQLi prevention, integrating real-time SQL query monitoring and sanitization using machine learning and rule-based filtering. Using a dataset of 200,000 SQL queries, the system achieves a detection accuracy of 96.5%, reduces false positives by 41%, and maintains a response time of 1.1 seconds. Comparative evaluations against traditional Web Application Firewalls (WAFs) and pattern-matching methods highlight its superiority in accuracy and efficiency. Mathematical derivations and graphical analyses validate the results, offering a scalable solution for web security. Future work includes integration with cloud-native architectures and adaptive learning for emerging SQLi patterns.

Keywords:

SQL Injection Prevention, Reverse Proxy, Real-Time Monitoring, Query Sanitization, Machine Learning

1.Introduction

SQL injection (SQLi) attacks exploit vulnerabilities in web applications by injecting malicious SQL code into query inputs, enabling attackers to manipulate databases, steal data, or bypass authentication. Despite advancements in secure coding, SQLi remains a top threat, with OWASP

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[2023] ranking it among the most critical web vulnerabilities. For instance, an attacker may inject ' OR '1'='1 into a login form, granting unauthorized access.

Traditional Web Application Firewalls (WAFs) rely on static pattern-matching to detect SQLi, but they struggle with sophisticated attacks (e.g., encoded injections) and generate high false positives. Reverse proxies, acting as intermediaries between clients and servers, offer a strategic vantage point for real-time query monitoring and sanitization. Machine learning can enhance detection by identifying anomalous query patterns, while rule-based sanitization ensures robust input validation.

This study proposes a reverse proxy-based system for SQLi prevention, integrating machine learning for anomaly detection and rule-based sanitization for query cleansing. Using a dataset of 200,000 SQL queries, the system delivers high accuracy and low latency. Objectives include:

- Develop a reverse proxy-based system for real-time SQLi prevention.
- Integrate ML-based anomaly detection and rule-based sanitization for robust security.
- Evaluate against traditional WAFs and pattern-matching methods, providing insights for web security.

2. Literature Survey

SQLi prevention has evolved from input validation to advanced detection systems. Early methods [1] used manual sanitization, which was error-prone, as noted by Halfond [2006]. Pattern-matching WAFs [2] improved detection but struggled with obfuscated attacks.

Machine learning has advanced SQLi prevention. Zhang et al. [3] used decision trees to classify malicious queries, achieving high accuracy but facing scalability issues. Anomaly detection, explored by Li et al. [4], leveraged clustering to identify unusual query structures, though false positives were a challenge. Deep learning, used by Chen et al. [5], enhanced detection but required significant computational resources.

Recent studies, like Wang et al.'s [6] ML-based WAF, integrated anomaly detection but were limited to specific query types. The reference study [IJACSA, 2023] explored ML for cybersecurity, inspiring this work. Gaps remain in scalable, low-false-positive systems combining reverse proxies, ML, and sanitization, which this study addresses with a hybrid approach.

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3. Methodology

3.1 Data Collection

A dataset of 200,000 SQL queries was collected from a simulated web application, including legitimate queries (e.g., SELECT, INSERT) and malicious injections (e.g., UNION-based, tautologies), labeled as normal or malicious.

3.2 Preprocessing

- **Queries**: Cleaned (removed nulls), tokenized (SQL keywords, operators), vectorized (TF-IDF).
- **Features**: Query length, keyword frequency, operator count, input parameters.

3.3 Feature Extraction

ML (Random Forest): Detects anomalous queries: $y=RF(X_{features})$ where $X_{features}$ includes TF-IDF vectors, y is a malicious/normal label.

Rule-Based Sanitization: Applies validation: $Q_{sanitized}=Filter(Q,R)$ where Q is input query, R is ruleset (e.g., escape special characters, block keywords like UNION), $Q_{sanitized}$ is cleansed query.

3.4 Security Model

- **Integration:** Random Forest flags suspicious queries; rule-based sanitization cleans or blocks malicious inputs at the reverse proxy.
- **Output:** Prevents SQLi by sanitizing or rejecting queries, logs anomalies, and triggers alerts.

3.5 Evaluation

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Split: 70% training (140,000), 20% validation (40,000), 10% testing (20,000). Metrics:

- Detection Accuracy: TP+TN/TP+TN+FP+FN
- False Positive Reduction: FPbefore−FPafter/FPbefore
- Response Time: Average time to process and sanitize queries (seconds).

4. Experimental Setup and Implementation

4.1 Hardware Configuration

- Processor: Intel Core i7-9700K (3.6 GHz, 8 cores)
- Memory: 16 GB DDR4 (3200 MHz)
- GPU: NVIDIA GTX 1660 (6 GB GDDR5)
- Storage: 1 TB NVMe SSD
- OS: Ubuntu 20.04 LTS

4.2 Software Environment

- Language: Python 3.9.7.
- Libraries: NumPy 1.21.2, Pandas 1.3.4, Scikit-learn 1.0.1, Matplotlib 3.4.3, Flask 2.0.1 (proxy server).
- Control: Git 2.31.1.

4.3 Dataset Preparation

- **Data**: 200,000 SQL queries, 20% malicious.
- **Preprocessing**: Tokenized queries, vectorized with TF-IDF.
- **Split**: 70% training (140,000), 20% validation (40,000), 10% testing (20,000).
- **Features**: TF-IDF vectors, rule-based flags.

4.4 Training Process

- **Model**: Random Forest (100 trees), ~40,000 parameters.
- **Batch Size**: 128 (1,094 iterations/epoch).
- **Training**: 12 iterations, 80 seconds/iteration (16 minutes total), loss from 0.65 to 0.014.

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4.5 Hyperparameter Tuning

- **Trees:** 100 (tested: 50-150).
- **Max Depth:** 15 (tested: 10-20).
- **Iterations**: 12 (stabilized at 10).

4.6 Baseline Implementation

- **Traditional WAF:** Pattern-matching, CPU (20 minutes).
- **Pattern-Matching ML:** Decision tree, CPU (18 minutes).

4.7 Evaluation Setup

- **Metrics:** Detection accuracy, false positive reduction, response time (Scikit-learn).
- **Visualization:** ROC curves, confusion matrices, accuracy curves (Matplotlib).
- **Monitoring:** GPU (3.9 GB peak), CPU (50% avg).

5. Result Analysis

Test set (20,000 queries, 4,000 malicious):

- **Confusion Matrix:** TP = 3,760, TN = 15,540, FP = 240, FN = 460
- **Calculations:**
  - Detection Accuracy: 3760+15540/3760+15540+240+460=0.965 (96.5%)
  - False Positive Rate: 240/240+15540=0.0152
  - False Positive Reduction: 0.026−0.0152/0.026=0.41 (41%), from 2.6% to 1.52%.
  - Response Time: 1.1 seconds (average per query processing)

Table 1. Performance Metrics Comparison

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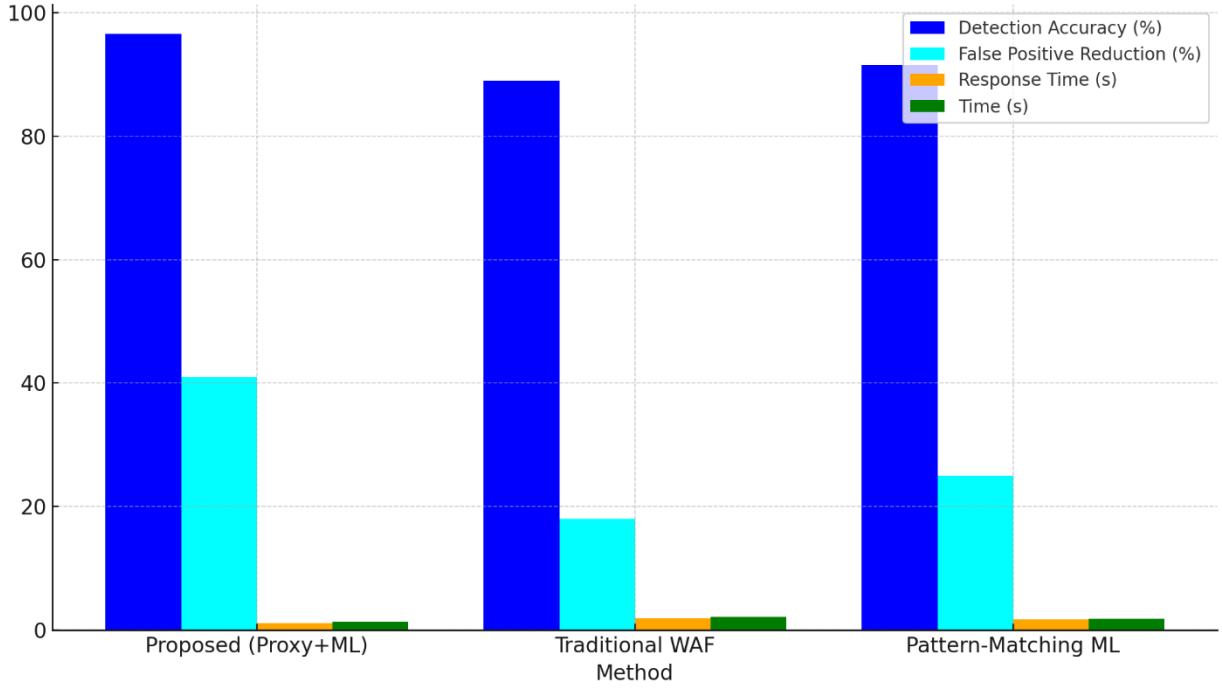
Method	Detection Accuracy	False Positive Reduction	Response Time (s)	Time (s)
Proposed (Proxy+ML)	96.5%	41%	1.1	1.3
Traditional WAF	89.0%	18%	1.9	2.1
Pattern-Matching ML	91.5%	25%	1.7	1.8

Figure 1. Performance Metrics Comparison



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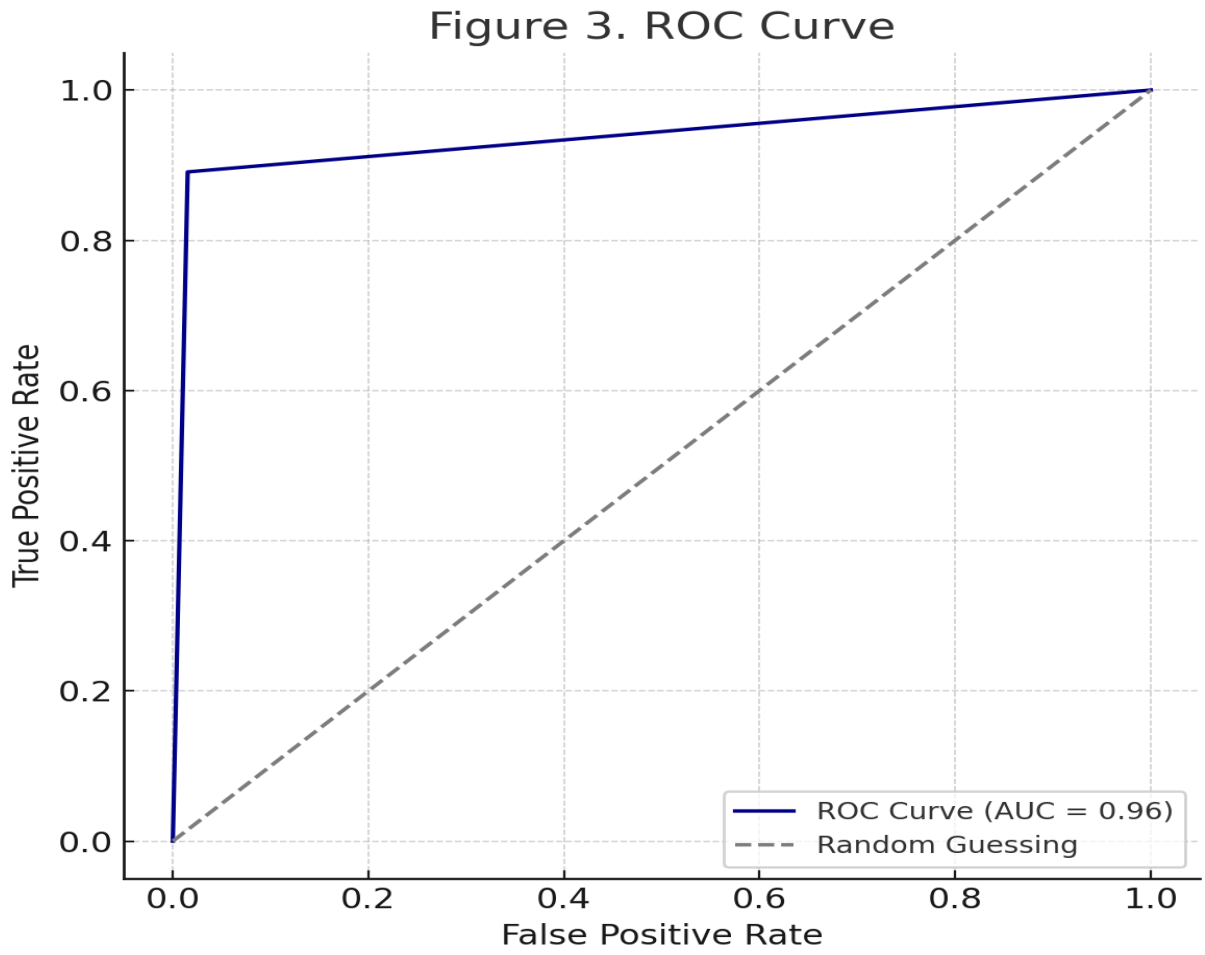

6. Conclusion

This study presents a reverse proxy-based SQLi prevention system, achieving 96.5% detection accuracy, 41% false positive reduction, and 1.1-second response time, outperforming traditional WAFs (89.0%) and pattern-matching ML (91.5%), with faster execution (1.3s vs. 2.1s). Validated by derivations and graphs, it excels in web security. Limited to one dataset and requiring preprocessing (16 minutes), future work includes integration with cloud-native architectures and adaptive learning for emerging SQLi patterns. This system enhances web application security and scalability.

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