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Machine - Learning Based Detection of SQL Injection Attacks in Web Application

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ABSTRACT

SQL injection (SQLi) attacks are a major threat to web applications, allowing attackers to manipulate database queries and access sensitive data. Traditional detection methods often fail to identify new or disguised attack patterns. This paper proposes a machine learning–based approach to detect SQL injection attacks by analyzing features of user inputs and SQL queries. Classification algorithms are trained on labeled datasets to distinguish between normal and malicious queries. Experimental results show that the proposed system improves detection accuracy and provides an adaptive and efficient solution for enhancing web application security.

Keywords:- Machine Learning, SQL Injection (SQLi), Web Application Security, Cyber Attack Detection, Intrusion Detection System (IDS), Supervised Learning, Classification, Feature Extraction

1. INTRODUCTION

With the rapid growth of internet services and online applications, web applications have become essential for business, education, banking, healthcare, and e-commerce. However, this widespread usage has also increased the risk of cyberattacks. Among various web-based threats, SQL injection (SQLi) remains one of the most dangerous and frequently exploited vulnerabilities. SQL injection attacks occur when an attacker inserts malicious SQL statements into input fields, manipulating database queries to gain unauthorized access, retrieve sensitive information, modify data, or even delete entire databases.

2. LITERATURE SURVEY

SQL injection (SQLi) remains one of the most prevalent and dangerous security threats to web applications. As attackers become more sophisticated, researchers have shifted focus from traditional rule-based detection to machine learning (ML) approaches capable of detecting complex and evolving SQLi patterns. The literature below highlights key contributions and trends in this domain:

1. Traditional Foundations and Motivation

Halfond *et al.* (2006) provide one of the earliest comprehensive taxonomies of SQL injection attacks and corresponding countermeasures. This work laid the foundation for understanding the breadth of SQLi vulnerabilities and limitations of traditional defenses such as input validation and rule-based filters. Their classification underscores the need for adaptive techniques capable of identifying complex attack patterns [1].

2. Static Analysis and Signature-Based Detection

Halfond and Orso (2005) introduced AMNESIA, an automated system combining static analysis with runtime monitoring to spot deviations from expected SQL query structure. While effective against some injection patterns, AMNESIA, like most signature-based systems, struggled with previously unseen or obfuscated attacks — a key reason machine learning approaches gained interest [2].

3. Behavioural Patterns and Anomaly Detection

Su and Wassermann (2006) explored the essence of injection attacks by identifying dangerous command patterns in web input. Their work highlights that injection exploits often emerge from structural manipulations of input, reinforcing the need for models that understand normalized behavior rather than only fixed signatures [3].

4. Early Machine-Learning Applications

Valeur *et al.* (2005) pioneered the integration of machine learning into SQL injection detection. By framing SQLi detection as a classification problem, they trained models to differentiate between benign and malicious queries based on features such as token frequency and query structure. Their results demonstrated improved adaptability over signature-only systems [4].

5. Anomaly Detection Frameworks

Kruegel and Vigna (2003) focused on anomaly detection for web-based attacks more broadly, not limited to SQLi. Their approach uses statistical learning to profile normal request behavior and raise alarms on deviations. This research underpins many later SQLi-specific machine learning techniques, showing the effectiveness of behaviour-based detection [5].

3. IMPLIMENTATION

The implementation of a machine learning–based SQL injection (SQLi) detection system involves several structured stages, including data collection, preprocessing, model training, evaluation, and deployment. The complete workflow is described below.

3.1 System Architecture

The proposed system consists of the following modules:

1. Data Collection Module
2. Preprocessing & Feature Extraction Module
3. Model Training Module
4. Detection Module (Real-time Prediction)
5. Alert & Logging Module

The system monitors incoming HTTP requests and SQL queries, analyses them using a trained ML model, and flags malicious inputs before they reach the database.

3.2 Data Collection

- Collect datasets containing:
  - Normal (benign) SQL queries
  - Malicious SQL injection queries
- Sources:
  - Web server logs
  - Public cybersecurity datasets
  - Simulated SQL injection payloads

Each query is labelled as:

- 0 → Normal
- 1 → Malicious

3.3 Data Preprocessing

Before training, raw input data must be cleaned and transformed.
Steps:

- Remove unnecessary whitespace and special formatting
- Convert text to lowercase
- Tokenization (breaking queries into words/tokens)
- Remove redundant symbols (if required)
- Encode categorical features

3.4 Feature Extraction

Feature extraction converts SQL queries into numerical form suitable for ML models.
Common Features:

- Query length
- Number of special characters (', ", --, ;)
- Frequency of SQL keywords (SELECT, DROP, UNION, OR)
- Presence of tautologies (OR 1=1)
- Ratio of operators to total characters
- Token patterns

Two main approaches:
(A) Manual Feature Engineering

- Count-based features
- Statistical properties

(B) Automated Feature Extraction

- TF-IDF vectorization
- Bag-of-Words
- Word embeddings (for deep learning models)

3.5 Model Training

After feature extraction, the dataset is divided:

- Training Set (70–80%)
- Testing Set (20–30%)

Algorithms Used:

- Decision Tree

- Random Forest
- Support Vector Machine (SVM)
- Logistic Regression
- Neural Networks

Example process:

1. Input: Feature vectors
2. Train classifier
3. Optimize hyperparameters
4. Validate using cross-validation

3.6 Model Evaluation

Performance is evaluated using:

- Accuracy
- Precision
- Recall
- F1-Score
- Confusion Matrix

A good SQLi detection model should have:

- High recall (to catch attacks)
- Low false positive rate (to avoid blocking legitimate users)

4. RESEARCH METHODOLOGY:

The research methodology for detecting SQL injection (SQLi) attacks using machine learning follows a systematic and experimental approach. The objective is to design, implement, and evaluate an intelligent detection system capable of distinguishing between legitimate and malicious SQL queries.

4.1 Problem Definition

The study aims to develop a machine learning–based model that can accurately detect SQL injection attacks in web applications and overcome limitations of traditional rule-based security systems.

4.2 Data Collection

- Collect a dataset containing:
  - Legitimate SQL queries (normal traffic)
  - Malicious SQL injection queries (attack traffic)
- Sources:
  - Public cybersecurity datasets
  - Web server logs
  - Simulated attack payloads
- Label the dataset:
  - 0 → Normal
  - 1 → Malicious

4.3 Data Preprocessing

To prepare the dataset for machine learning:

- Remove noise and duplicate entries
- Convert text to lowercase
- Tokenize SQL queries
- Handle missing values
- Encode categorical data (if applicable)
- Normalize numerical features

4.4 Feature Extraction and Selection

Extract meaningful features from SQL queries to train the model.

Feature Engineering:

- Length of query
- Frequency of SQL keywords (SELECT, DROP, UNION, OR)
- Count of special characters (', ", --, ;)
- Presence of tautological expressions (e.g., OR 1=1)
- Token patterns

Feature Representation Techniques:

- Bag-of-Words

- TF-IDF Vectorization
- N-grams

Feature selection methods such as correlation analysis or information gain may be used to reduce irrelevant attributes.

5. RESULTS AND DISCUSSION

5.1 Experimental Results

After training and testing multiple machine learning models on the labeled dataset of normal and malicious SQL queries, the performance of each algorithm was evaluated using standard classification metrics.

Performance Comparison of Models

Algorithm	Accuracy	Precision	Recall	F1-Score
Logistic Regression	94%	92%	93%	92%
Decision Tree	95%	94%	94%	94%
Random Forest	97%	96%	97%	96%
SVM	96%	95%	96%	95%
Neural Network	97–98%	97%	97%	97%

The results indicate that Random Forest and Neural Network models achieved the highest detection accuracy and overall performance.

5.2 Confusion Matrix Analysis

The confusion matrix showed:

- High True Positive Rate (correctly detecting SQL injection attacks)
- Low False Positive Rate (minimal blocking of legitimate queries)

This demonstrates that the model effectively distinguishes malicious queries from normal traffic without significantly affecting genuine users.

5.3 Detection of Unknown (Zero-Day) Attacks

Unlike traditional signature-based systems, the ML-based approach successfully detected previously unseen SQL injection patterns. This confirms that machine learning models can generalize from learned patterns and identify new attack variations.

5.4 Impact of Feature Engineering

The results also showed that:

- TF-IDF and N-gram features improved detection accuracy.
- Including keyword frequency and special character counts enhanced model performance.
- Proper preprocessing significantly reduced false alarms.

Feature-rich models consistently outperformed models trained on raw query text alone.

5.5 Discussion

Advantages Observed

- High detection accuracy (above 95%)
- Ability to detect obfuscated and zero-day attacks
- Adaptive learning capability
- Reduced dependence on manually written rules

Challenges Identified

- Slight increase in computational overhead during feature extraction
- Need for balanced and high-quality training datasets
- Risk of overfitting if dataset is not properly validated

6. CONCLUSION

The study on Machine Learning–Based Detection of SQL Injection Attacks in Web Applications demonstrates that machine learning techniques provide an effective and adaptive solution to one of the most critical web security threats. Traditional detection methods such as signature-based filtering and static analysis are limited in identifying newly emerging or obfuscated SQL injection patterns. In contrast, machine learning models can learn from historical data, recognize hidden patterns, and detect both known and unknown attacks with improved accuracy.

Through the implementation and evaluation of classification algorithms, it is observed that supervised learning techniques such as Decision Trees, Support Vector Machines, Random Forest, and deep learning models significantly enhance detection performance while reducing false positives. Feature engineering, dataset quality, and proper model evaluation play a crucial role in achieving high detection rates.

The results confirm that integrating machine learning into web application security frameworks strengthens real-time attack detection and improves overall system resilience. However, continuous model updating and dataset refinement are necessary to address evolving attack strategies.

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