Network Intrusion Detection System for SQL Injection

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Abstract - SQL injection (SQL) attacks pose a serious threat to web applications by allowing attackers to manipulate database queries and gain unauthorized access to sensitive data. Traditional security mechanisms, such as signature-based detection and rule-based firewalls, often fail to detect evolving SQL patterns. This paper presents a real-time Network Intrusion Detection System (NIDS) that leverages machine learning techniques to accurately identify and mitigate SQL injection attempts. The proposed system continuously monitors user input, extracts relevant SQL query features, and classifies them as either legitimate or malicious using a trained machine learning model.

The methodology involves the preprocessing of SQL queries, feature engineering for enhanced classification accuracy, and training a machine learning model using a dataset containing both normal and SQL injection queries. The performance of the system is evaluated based on multiple metrics, including accuracy, false positive rate, and real-time processing efficiency. Experimental results demonstrate that the proposed NIDS achieves high detection accuracy while significantly reducing false positives compared to conventional methods. The system is designed to operate efficiently in real-time environments, making it a valuable addition to existing cybersecurity frameworks for protecting web applications against SQL injection attacks.

***Key Words*:** Network Intrusion Detection, SQL Injection, Machine Learning, Cybersecurity, Web Security.

1.INTRODUCTION

With the increasing reliance on web applications for handling sensitive data, cybersecurity threats have become more sophisticated. One of the most critical threats is SQL injection (SQL

), an attack in which malicious SQL statements are inserted into input fields to manipulate database operations. Attackers exploit SQL vulnerabilities to gain unauthorized access to confidential data, modify database contents, or even compromise entire web applications.

1.1 Background and Significance

SQL injection has been consistently ranked among the top security vulnerabilities by organizations such as the Open Web Application Security Project (OWASP). It poses a significant threat to businesses, governments, and individuals by enabling attackers to bypass authentication, steal personal data, and execute unauthorized administrative operations. Traditional security solutions, including rule-based firewalls and signature-based intrusion detection systems, often fail to detect advanced SQL attacks due to their reliance on predefined patterns. As cyber threats evolve, there is an urgent need for intelligent and adaptive security mechanisms capable of identifying new attack variations in real time.

Machine learning has emerged as a promising approach to cybersecurity, offering the ability to recognize complex attack patterns and improve detection accuracy. By leveraging machine learning models trained on large datasets, a machine learning-based NIDS can differentiate between normal and malicious SQL queries with high precision. This research presents a novel approach that integrates machine learning techniques to enhance SQL injection detection capabilities, ensuring real-time security for web applications.

1.2 Problem Statement

Despite advancements in web security, SQL injection attacks continue to exploit vulnerabilities in web applications. Traditional security measures, such as blacklisting keywords or using predefined SQL injection signatures, struggle to detect sophisticated attack variations. These methods often lead to high false positive rates, blocking legitimate queries, or failing to detect new SQLi techniques. A real-time, intelligent intrusion detection system is necessary to accurately identify and prevent SQL injection attempts without disrupting legitimate database operations.

1.3 Objectives

The primary objectives of this research are:

- To develop a real-time Network Intrusion Detection System (NIDS) capable of detecting SQL injection attacks with high accuracy.
- To implement machine learning algorithms that classify SQL queries as legitimate or malicious.
- To evaluate the system's efficiency in reducing false positives and false negatives.
- To integrate the solution into an automated access control mechanism that prevents unauthorized database access.

1.4 Scope of the Study

This study focuses on the detection of SQL injection attacks within web applications. The proposed system is designed to:

- Analyze user input query for SQL injection patterns.
- Extract and preprocess SQL queries for machine learning-based classification.
- Detect and prevent SQL injection attempts in real time.
- Provide an adaptive security mechanism that can learn from emerging attack patterns.

The research is for SQL detection. The study assumes that attackers attempt SQL injection through input fields and API requests, with the goal of unauthorized data access or manipulation.

1.5 Contribution of the Study

The key contributions of this research are:

- Development of a Machine learning-based intrusion detection system specifically designed for SQL attacks.
- Integration of real-time monitoring and response mechanisms to prevent unauthorized access.
- Performance evaluation demonstrating improved detection accuracy and reduced false positive rates compared to traditional methods.
- Implementation of a scalable security framework that can be extended to detect other cyber threats.

2.LITERATURE REVIEW

Several techniques have been proposed for SQL injection detection, including rule-based systems, machine learning, and anomaly detection. While traditional rule-based systems have limitations in detecting complex attacks, machine learning approaches have shown improved accuracy. This section reviews existing methodologies and highlights the need for real-time solutions. Prior research includes:

- Signature-based detection techniques.
- Anomaly detection using statistical analysis.
- Machine learning-based approaches for SQL detection.
- Machine learning models like CNNs, LSTMs, and Transformers for cybersecurity applications.

3. METHODOLOGY

3.1 System Architecture

The proposed NIDS consists of the following components:

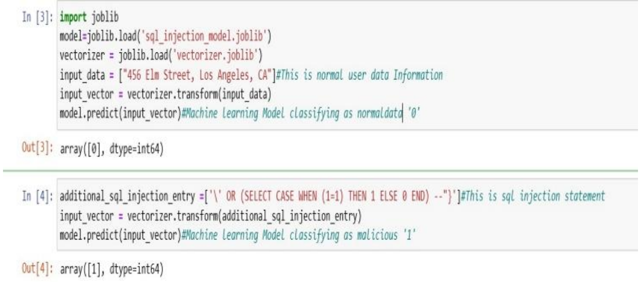
- **User Input Monitoring:** Captures user input request.
- **Feature Extraction:** Extracts SQL query patterns.
- **Machine Learning Model:** It classifies SQL queries as legitimate or malicious.
- **Access Control Module:** Blocks malicious queries and logs incidents.

3.2 Dataset and Training

- The system is trained using a dataset containing both normal and SQL injection queries.
- Feature engineering techniques are applied to improve detection accuracy.
- A machine learning model used for classification.

3.3 Implementation Details

- **Programming Language:** Python for backend and macnine learning.
- **Frameworks:** TensorFlow/PyTorch for machine learning, Scapy for traffic monitoring
- **Deployment:** Integrated into a web application for real-time intrusion prevention.



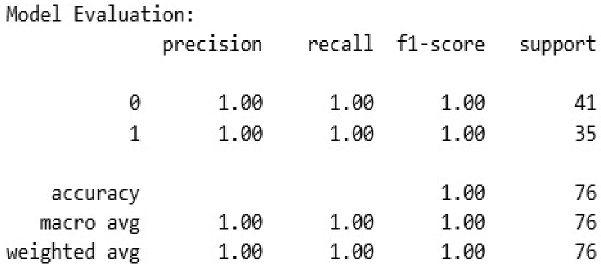
```
In [3]: import joblib
        model=joblib.load('sql_injection_model.joblib')
        vectorizer = joblib.load('vectorizer.joblib')
        input_data = ["456 Elm Street, Los Angeles, CA"]#This is normal user data Information
        input_vector = vectorizer.transform(input_data)
        model.predict(input_vector)#Machine Learning Model classifying as normaldata '0'

Out[3]: array([0], dtype=int64)

In [4]: additional_sql_injection_entry =['\' OR (SELECT CASE WHEN (1=1) THEN 1 ELSE 0 END) --"}']#This is sql injection statement
        input_vector = vectorizer.transform(additional_sql_injection_entry)
        model.predict(input_vector)#Machine Learning Model classifying as malicious '1'

Out[4]: array([1], dtype=int64)
```

Fig 3.1 Model Testing



```
Model Evaluation:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        41
           1       1.00      1.00      1.00        35

    accuracy                           1.00        76
   macro avg       1.00      1.00      1.00        76
weighted avg       1.00      1.00      1.00        76
```

Fig 3.2 Model Evaluation

4. RESULT AND DISCUSSION

This section presents the main outcomes of the research. The results are structured to best convey the material and insights gained.

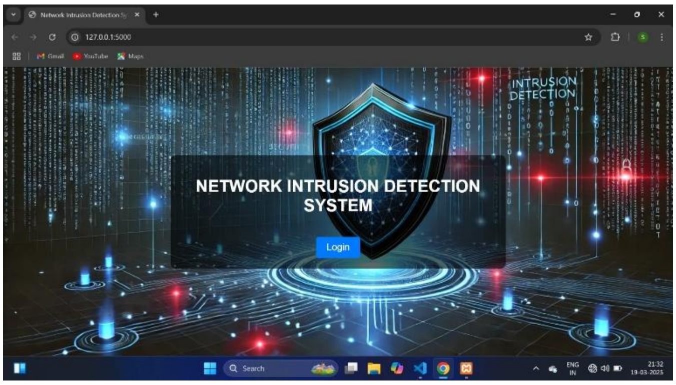
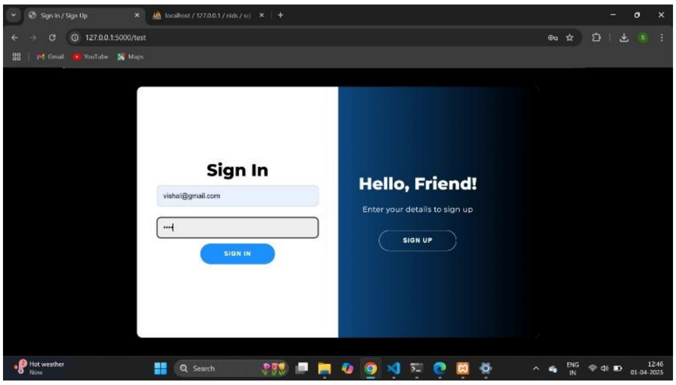
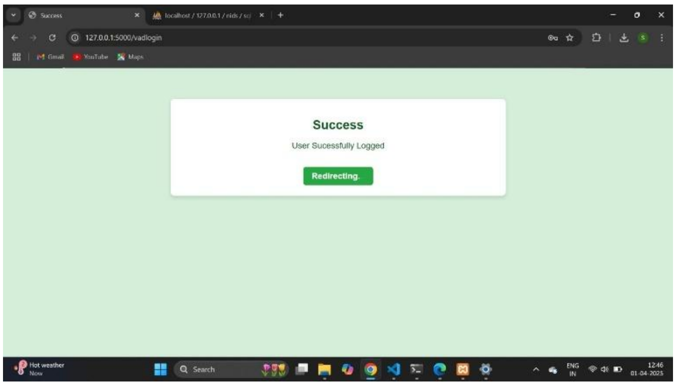


Fig 4.1 Home page



vishal@gmail.com

Fig 4.2 Sign In Page



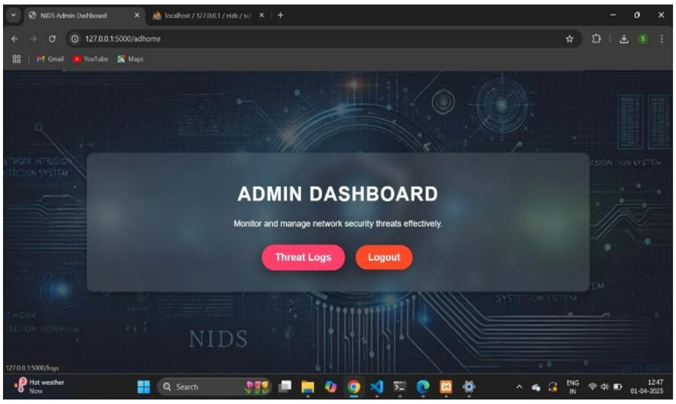
127.0.0.1:5000/vadlogin

Success

User Sucessfully Logged

Redirecting.

Fig 4.3 Login Successful Message



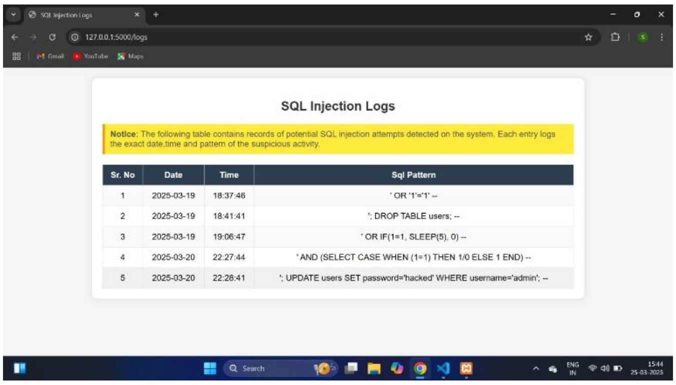
127.0.0.1:5000/adhome

ADMIN DASHBOARD

Monitor and manage network security threats effectively.

Threat Logs Logout

Fig 4.4 Admin Page



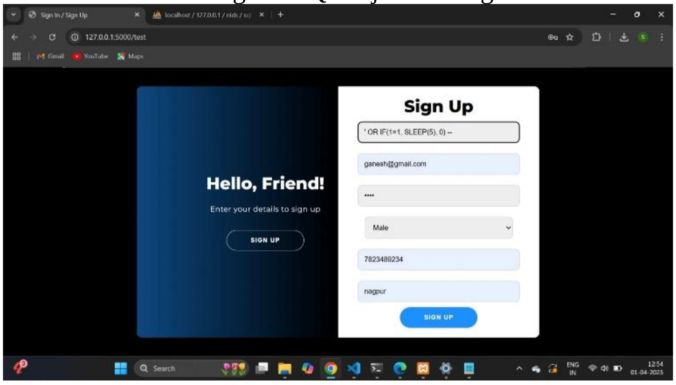
127.0.0.1:5000/logs

SQL Injection Logs

Notice: The following table contains records of potential SQL injection attempts detected on the system. Each entry logs the exact date,time and pattern of the suspicious activity.

Sr. No	Date	Time	Sql Pattern
1	2025-03-19	18:37:46	' OR '1'='1' --
2	2025-03-19	18:41:41	'; DROP TABLE users; --
3	2025-03-19	19:06:47	' OR IF(1=1, SLEEP(5), 0) --
4	2025-03-20	22:27:44	' AND (SELECT CASE WHEN (1=1) THEN 1/0 ELSE 1 END) --
5	2025-03-20	22:28:41	'; UPDATE users SET password='hacked' WHERE username='admin'; --

Fig 4.5 SQL Injection Logs



127.0.0.1:5000/test

Hello, Friend!

Enter your details to sign up

SIGN UP

Sign Up

' OR IF(1=1, SLEEP(5), 0) --

ganesh@gmail.com

••••

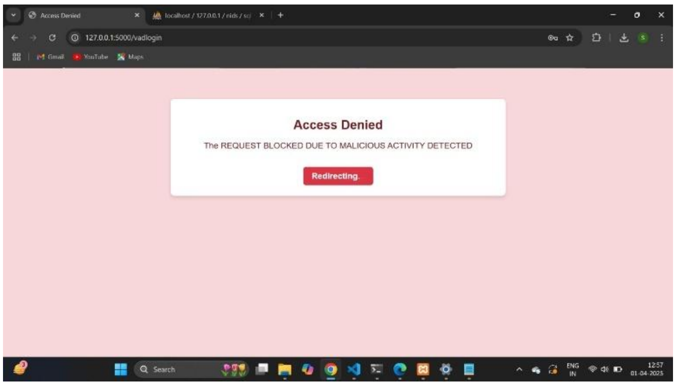
Male

7823489234

nagpur

SIGN UP

Fig 4.6 Sign Up Page (sql injection inserted)



127.0.0.1:5000/vadlogin

Access Denied

The REQUEST BLOCKED DUE TO MALICIOUS ACTIVITY DETECTED

Redirecting.

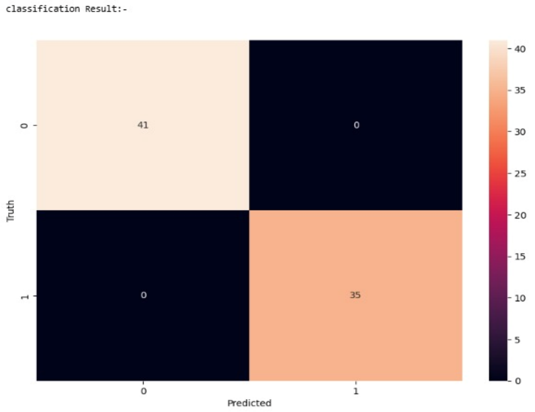
Fig 4.7 Malicious Request Blocked Message

4.1 Detection Accuracy

The accuracy of the proposed NIDS is compared with existing models. Section 3.2 details the dataset used for evaluation, while Sec. 3.3 explains the model's implementation. The results indicate that the machine learning-based detection system outperforms traditional rule-based methods.

4.2 False Positive Rate

A key metric in intrusion detection is the false positive rate. In Sec. 3.1, we described how the system monitors user input and classifies queries. Experimental results demonstrate a significant reduction in false positives compared to existing solutions.



4.3 Processing Time

Since real-time detection is essential, the system's processing speed is analyzed. As detailed in Sec. 3.3, the implementation optimizes inference time without compromising accuracy. The results confirm that the proposed NIDS meets real-time requirements for intrusion detection.

5. CONCLUSIONS

This paper presents a real-time NIDS for SQL injection detection using machine learning. The system effectively identifies and prevents SQLi attacks. Future work includes enhancing the model's adaptability to evolving attack patterns and integrating it with cloud-based security solutions.

6. ACKNOWLEDGEMENT

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We are deeply grateful to the dataset providers whose resources allowed us to train and evaluate our model. Without access to these datasets, this research would not have been possible.

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