A

Major Project Report

On

DEFENSE STRATEGIES FOR EPIDEMIC CYBER SECURITY THREATS: MODELING AND ANALYSIS BY USING A MACHINE LEARNING APPROACH

Submitted to CMREC (UGC Autonomous), Affiliated to JNTUH

In Partial Fulfillment of the requirements for the Award of Degree of

BACHELOR OF TECHNOLOGY IN

COMPUTER SCIENCE AND ENGINEERING

(Artificial Intelligence & Machine Learning)

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CERTIFICATE

This is to certify that the project entitled **"Defense Strategies for Epidemic Cyber Security Threats: Modeling and Analysis by using a Machine Learning Approach"** is a bonafide work carried out by

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in partial fulfillment of the requirement for the award of the degree of **BACHELOR OF TECHNOLOGY** in **COMPUTER SCIENCE AND ENGINEERING (AI&ML)** from CMR Engineering College, under our guidance and supervision.

The results presented in this project have been verified and are found to be satisfactory. The results embodied in this project have not been submitted to any other university for the award of any other degree or diploma.

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This is to certify that the work reported in the present Major project entitled **"DEFENSE STRATEGIES FOR EPIDEMIC CYBER SECURITY THREATS: MODELING AND ANALYSIS BY USING A MACHINE LEARNING APPROACH"** is a record of bonafide work done by us in the Department of Computer Science and Engineering (AI&ML), CMR Engineering College. The reports are based on the project work done entirely by us and not copied from any other source. We submit our project for further development by any interested students who share similar interests to improve the project in the future.

The results embodied in this Major project report have not been submitted to any other University or Institute for the award of any degree or diploma to the best of our knowledge and belief.

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ABSTRACT

With the rapid growth of digital technologies, internet-based applications, and interconnected network systems, cyber security has become a major concern in modern computing environments. The increasing use of cloud computing, IoT devices, and online platforms has significantly improved efficiency and accessibility, but it has also introduced multiple vulnerabilities that can be exploited by attackers. Cyber threats such as SQL Injection, Cross-Site Scripting (XSS), malicious URLs, phishing, and distributed denial-of-service (DDoS) attacks have become more frequent, sophisticated, and difficult to detect. These attacks can spread rapidly across networks, similar to epidemic diseases, causing serious damage such as data breaches, financial loss, service disruption, and compromise of sensitive information. Traditional security mechanisms, which rely on predefined rules and signature-based detection techniques, are not sufficient to identify new and evolving attack patterns, making them ineffective in dynamic environments. To address these challenges, this project presents an intelligent and efficient approach for analyzing, detecting, and controlling cyber security threats using a combination of mathematical modeling and machine learning techniques. The system models the spread of cyber threats using the SEIAR compartmental model, which categorizes systems into different states such as susceptible, exposed, infected, asymptomatic, and recovered, allowing a structured analysis of how attacks propagate through interconnected networks. In addition, machine learning algorithms are employed to analyze input data such as SQL queries, scripts, and URLs, enabling the system to classify inputs as malicious or benign with high accuracy.

KEYWORDS: Cyber Security, Machine Learning, SQL Injection, Cross-Site Scripting (XSS), Malicious URL Detection, Intrusion Detection, Data Preprocessing, Feature Extraction, Classification, Threat Detection

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1. INTRODUCTION

1.1 Introduction

In recent years, rapid technological advancement has significantly improved the efficiency and performance of various industries. Software systems are widely used in sectors such as healthcare, agriculture, communication, and robotics, enabling faster processing and better decision-making. However, this increased dependency on technology has also introduced serious security challenges, especially in the form of cyberattacks **[4][14]**.

Cyberattacks such as malware, phishing, denial-of-service (DoS), and distributed denial-of-service (DDoS) attacks can spread quickly across interconnected systems, similar to the way infectious diseases spread among individuals **[15]**. These attacks can damage systems, disrupt services, and lead to loss of sensitive data. With the growth of technologies like IoT and Industry 4.0, the risk of such attacks has increased further due to the high level of connectivity between devices **[3][14]**.

Machine learning techniques, particularly Artificial Neural Networks and deep learning models, are widely used to detect cyber threats and analyze complex system behaviors more efficiently **[5][10]**. These techniques provide more accurate and adaptive solutions compared to traditional methods. By combining machine learning with intelligent analysis, the system can predict the behavior of cyber threats and assist in developing effective defense strategies **[2][15][28]**.

1.2 Project Objectives

- To study the behavior and spread of cyber security threats in interconnected systems.
- To develop a mathematical model (SEIAR) to represent the propagation of cyberattacks.
- To apply machine learning techniques for solving complex system equations.
- To analyze and predict the impact of cyber threats under different conditions.
- To improve early detection and response strategies for cyberattacks.
- To design and evaluate adaptive defense mechanisms that dynamically respond to evolving cyber threats using machine learning–driven insights from the SEIAR model.

1.3 Purpose of the Project

The primary purpose of this project is to develop an effective and intelligent approach for analyzing and controlling cyber security threats that spread rapidly across interconnected systems. In today's digital world, the usage of network-based applications, cloud computing, IoT devices, and online platforms has increased significantly **[3][14]**. While these technologies improve efficiency and connectivity, they also create multiple entry points for cyberattacks. As a result, cyber threats such as malware, ransomware, phishing, and distributed denial-of-service (DDoS) attacks have become more frequent, complex, and difficult to manage **[10][16]**.

Unlike traditional cyber threats, modern attacks behave in a manner similar to epidemic diseases, where a single infected system can quickly affect multiple devices across the network **[15]**. This rapid propagation makes it necessary to study cyber threats using structured and scientific approaches. Therefore, this project aims to use mathematical modeling techniques to represent and analyze the spread of cyberattacks. The SEIAR compartmental model is used to categorize devices into different states such as susceptible, exposed, infected, asymptomatic, and recovered **[15]**. This classification helps in understanding how attacks originate, spread, and eventually get controlled within a network environment.

Another important purpose of this project is to apply machine learning techniques for solving complex mathematical models. Traditional numerical methods are often time-consuming and may not provide efficient solutions for large-scale systems. To overcome this limitation, Artificial Neural Networks are used along with optimization algorithms such as the Levenberg-Marquardt algorithm **[2][5][19]**. These techniques help in obtaining accurate and faster solutions for the differential equations that describe the system. By comparing these results with standard methods like the Runge-Kutta approach, the system ensures reliability and accuracy in prediction.

The project also focuses on improving early detection and prediction of cyber threats. By analyzing patterns and behaviors of attacks, the system can forecast how a threat will spread over time. This predictive capability is essential for taking preventive actions before the attack causes

In addition, the project aims to identify vulnerable areas within a network. Cyberattacks often target weak points in the system, such as unsecured nodes, outdated software, or poorly configured networks. By studying the spread of attacks using the SEIAR model, the system can highlight these vulnerable regions and assist in strengthening the overall security infrastructure **[22][26]**. This enables organizations to take proactive measures and reduce the risk of future attacks.

Another key purpose is to design adaptive and intelligent defense strategies. Traditional security systems are mostly static and cannot effectively handle evolving threats. In contrast, machine learning-based systems can continuously learn from new data and update their behavior accordingly **[8][17]**. This adaptability allows the system to respond to new types of attacks and changing patterns, making it more effective in real-world scenarios.

The project also contributes to improving decision-making in cyber security management. By providing detailed analysis, predictions, and insights, the system helps security professionals understand the nature of threats and choose appropriate defense mechanisms. This leads to better planning, faster response, and more efficient handling of cyber incidents **[4][10]**.

Furthermore, the project emphasizes enhancing the overall resilience of network systems. Resilience refers to the ability of a system to withstand attacks and recover quickly from disruptions. By integrating mathematical modeling with machine learning techniques, the system ensures continuous monitoring, real-time analysis, and quick response to threats. This improves the reliability and stability of the network, even under adverse conditions **[14][28]**.

Overall, the purpose of this project is to develop a comprehensive, scalable, and intelligent cyber security solution that can effectively detect, analyze, predict, and control epidemic cyber threats. By combining mathematical models with advanced machine learning techniques, the project provides a strong foundation for improving cyber defense mechanisms and ensuring secure network operations in modern digital environments **[1][15]**.

1.4 Problem Statement

With the rapid growth of internet usage and digital applications, cyber security threats such as SQL Injection, Cross-Site Scripting (XSS), and malicious URLs have become increasingly common and sophisticated **[23][24][25].** These attacks can compromise sensitive data, disrupt services, and cause significant financial and reputational damage. Traditional security methods, which rely on predefined rules and signature-based detection, are not effective in identifying new and evolving attack patterns **[4][27].**

There is a need for an intelligent system that can automatically detect and classify cyber threats in real time. The challenge lies in analyzing large volumes of unstructured data such as queries, scripts, and URLs, which often contain complex and hidden patterns **[5][10].** Manual detection is time-consuming and prone to errors, making it unsuitable for modern cyber security requirements.

Therefore, the problem is to develop a machine learning-based system that can accurately identify malicious inputs and differentiate them from normal data **[11][19].** The system should be capable of handling diverse input formats, adapting to new types of attacks, and providing reliable results. This will help in improving security measures and reducing the risks associated with cyber threats **[1][28].**

1.5 Existing System and Disadvantages

In the current scenario, various methods and systems are used to detect and analyze cyber security threats. Most of these systems rely on mathematical modeling, traditional algorithms, or machine learning techniques to study the behavior of cyberattacks and predict their spread across networks **[4][15]**. One commonly used approach is the compartmental modeling technique, such as the SEIAR model, which categorizes devices into different states like susceptible, exposed, infected, asymptomatic, and recovered **[15]**. This model helps in understanding how cyber threats propagate within interconnected systems.

Existing systems also use numerical methods such as the Runge-Kutta algorithm to solve the differential equations that represent the spread of cyber threats. In addition, machine learning techniques, including Artificial Neural Networks and optimization algorithms like the Levenberg-Marquardt algorithm, are applied to improve prediction accuracy and analyze complex system behaviors **[5][19]**.

These approaches provide useful insights into cyberattack dynamics and help in designing basic defense mechanisms.

However, despite these advancements, current systems have several limitations. One major drawback is the high computational cost involved in solving complex mathematical models and processing large-scale network data **[10][17]**. These systems often require significant computational resources, making them less efficient for real-time applications.

Another limitation is the dependency on large datasets. Machine learning models require extensive training data to achieve accurate predictions. In many cases, obtaining high-quality and diverse datasets for cyber threats is challenging, which affects the performance and reliability of the system **[5][13]**.

Scalability is another concern, as some models are not suitable for large and complex networks with numerous interconnected devices. As the size of the network increases, the performance of these systems may degrade **[28]**.

Additionally, traditional systems lack adaptability and real-time response capabilities. They often fail to quickly detect and respond to rapidly spreading attacks, which can result in delayed action and increased damage **[1][24]**.

Overall, while existing systems provide a foundation for understanding and detecting cyber threats, they are limited by high computational requirements, lack of scalability, dependence on large datasets, and reduced adaptability to new and evolving cyberattacks. These limitations highlight the need for more efficient and intelligent systems **[15]**

DISADVANTAGES

- High computational cost due to complex mathematical modeling and algorithms.
- Requires large and high-quality datasets for training machine learning models.
- Limited ability to handle new or unknown types of cyberattacks.
- Poor generalization across different network environments.
- Scalability issues when applied to large and complex networks.
- Slower response time for rapidly spreading cyber threats.
- Lack of real-time adaptability to changing attack patterns.
- Dependence on specific models, making the system less flexible.

1.6 Proposed System and Advantages

The proposed system is designed to provide an efficient and intelligent solution for detecting, analyzing, and controlling cyber security threats that spread rapidly across networks. Unlike existing systems, this approach focuses on improving accuracy, adaptability, and real-time performance using machine learning techniques.

The system mainly targets different types of cyberattacks such as SQL Injection, Cross-Site Scripting (XSS), and Malicious URL attacks. It uses multiple machine learning algorithms to analyze input data and identify whether it is normal or malicious. By combining different models and techniques, the system improves detection capability and reduces false predictions.

With the rapid expansion of internet services, web applications, and online data exchange, cyber security threats have become more frequent and complex. Attacks such as SQL Injection, Cross-Site Scripting (XSS), and malicious URLs are widely used by attackers to exploit system

vulnerabilities, gain unauthorized access, and compromise sensitive information. These threats can lead to data breaches, financial losses, and disruption of services, making cyber security a critical concern in modern digital environments.

Traditional security mechanisms mainly rely on rule-based and signature-based detection methods. While these methods are effective for known threats, they fail to detect new and evolving attack patterns. As cyber threats continuously change, static detection systems are not sufficient to provide complete protection.

The proposed system overcomes these limitations by integrating machine learning models with preprocessing and feature extraction techniques to analyze complex input data efficiently. It supports real-time detection and adapts to new attack patterns by learning from data continuously. This makes the system more flexible and effective in handling modern cyber security challenges.

Furthermore, the proposed system incorporates an epidemic-based modeling approach, specifically the SEIAR (Susceptible–Exposed–Infected–Asymptomatic–Recovered) model, to simulate and understand the spread of cyber threats across interconnected systems. By treating cyberattacks as propagating entities similar to infectious diseases, the system can effectively analyze how vulnerabilities are exploited and how attacks spread within a network. This helps in identifying critical nodes that are more likely to be infected and require stronger protection mechanisms.

In addition to detection, the system emphasizes proactive defense strategies by integrating predictive analytics. Machine learning models are trained not only to classify attacks but also to forecast potential threat propagation patterns under different network conditions. This predictive capability enhances the system's ability to prevent attacks before they occur and improves overall network security management.

ADVANTAGES

- Uses multiple machine learning algorithms for improved accuracy.
- Combines models using ensemble techniques for better prediction performance.
- Provides real-time analysis and prediction of user inputs.
- Includes data preprocessing and feature extraction for better model performance.
- Reduces computational complexity compared to traditional methods.
- Adapts to new and evolving cyber threats using machine learning.
- Improves detection speed and reduces false positives.
- Scalable and suitable for large network environments.
- Enhances overall system security and reliability.

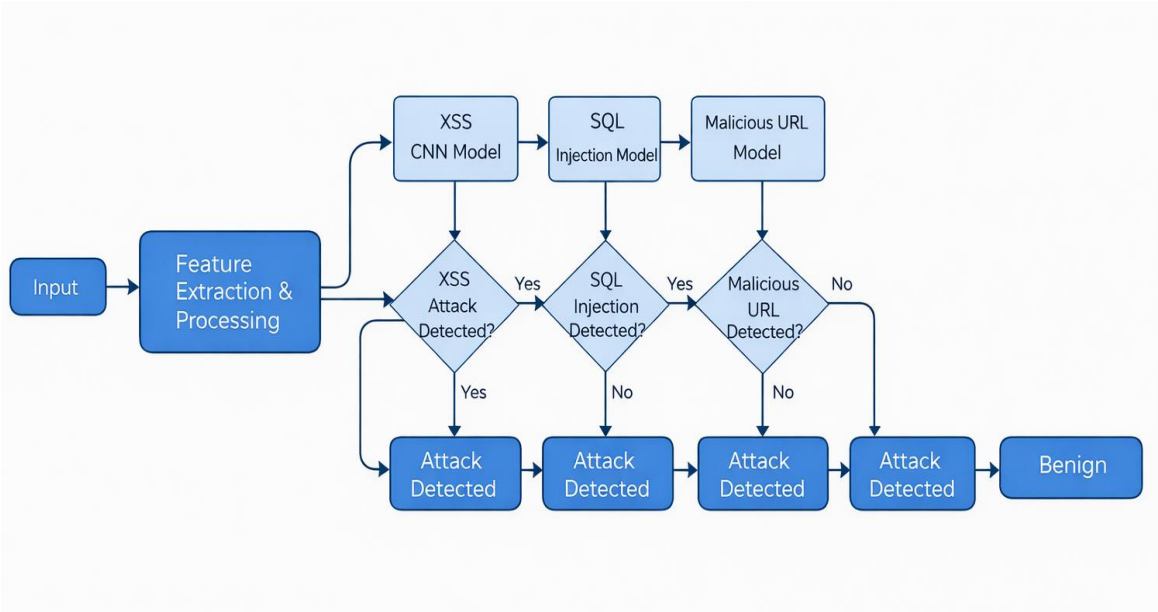


Fig 1.5.1: Block Diagram

1.7 Input Design and Output Design

1.7.1 Input Design

The system is designed to accept user inputs related to cyber security threats such as SQL queries, scripts, and URLs **[23][24][25]**. Since the system operates on user-provided data, the input layer is structured to handle different formats of textual input, including complex queries, embedded scripts, and varied URL patterns. The input may contain special characters, symbols, encoded strings, and irregular formats that are commonly associated with cyberattacks. Therefore, the input module is designed to manage diverse and unstructured data effectively **[5][10]**.

To ensure consistency and proper analysis, the input pipeline performs several preprocessing steps before passing the data to the machine learning models. These steps include cleaning unwanted characters, normalizing the text, handling special symbols, and converting the input into a structured format. Feature extraction techniques are then applied to transform the input into numerical representations suitable for model processing **[5][19]**. The system supports both labelled data during training and real-time unlabelled inputs during prediction.

By defining a clear input structure and applying necessary preprocessing techniques, the system improves reliability and reduces ambiguity. This ensures that the data is properly prepared for further analysis, leading to accurate detection of cyber threats **[11][12]**. The input design plays a key role in maintaining system efficiency and enabling smooth interaction between different modules.

Objectives

- A structured format is established for accepting user inputs such as SQL queries, scripts, and URLs, ensuring consistency and correctness.
- The input pipeline effectively removes noise, irrelevant characters, and inconsistencies, preparing the data for preprocessing and feature extraction.
- The system supports different types of inputs and formats, allowing accurate classification of various cyber threats such as SQL Injection, XSS, and malicious URLs.

1.7.2 Output Design

The output design defines how the results of the system are presented to the user after processing the input data. In this project, the system provides output in the form of classification results indicating whether the given input is malicious or benign. The output is generated after the input passes through preprocessing, feature extraction, and machine learning models **[5][10]**. Based on the analysis, the system displays results such as "SQL Injection Detected," "XSS Attack Detected," "Malicious URL," or "Benign" **[23][24][25]**.

The output is designed to be clear, simple, and easy to understand. Each module displays its result separately, allowing users to identify the type of threat detected. The system may also use visual indicators such as colors, where red represents a detected attack and green indicates safe input. This improves readability and helps users quickly interpret the result. The output is displayed in real time, ensuring immediate feedback for the user **[28]**.

The system ensures that the output is accurate and consistent with the input provided. It avoids ambiguity by clearly labeling the result and the type of attack. This helps users take appropriate actions to prevent potential security risks. The output design also supports future enhancements such as displaying confidence scores or detailed analysis reports, improving decision-making and system reliability **[11][14]**.

2. LITERATURE SURVEY

[1] D. Bala, A. Raihana Saboora, S. M. Samiksha and M. Shalini, *"Machine Learning Algorithms for Early Detection of Cybersecurity Threats,"* Journal of Emerging Technologies and Innovative Research (JETIR), vol. 13, no. 3, 2026. This study presents various machine learning algorithms for early detection of cyber security threats. It focuses on analyzing network behavior and identifying anomalies in real time. The proposed approach improves detection speed and accuracy while reducing false alarms. However, the model performance depends on dataset quality and may struggle with unseen attack patterns.

[2] Madhavi Pingili and B. Revathi, *"Optimal Foraging Algorithm for Adversarial Inversion Attacks in Wireless Networks for Analyzing Textual Data,"* Scopus Indexed Conference, 2026. This paper introduces an optimization-based approach for detecting adversarial attacks in wireless network environments. It uses algorithmic techniques to analyze complex data patterns and improve detection capability. The model enhances security by identifying hidden attack behaviours. However, it requires proper parameter tuning and may involve higher computational cost.

[3] V. Chaudhary, M. Desai and A. Chatterjee, *"Real-Time Intrusion Detection System for Vehicle Networks Using Machine Learning for Predictive Threat Analysis,"* SAE Technical Paper, 2026. This work proposes a real-time intrusion detection system using machine learning techniques for vehicle networks. It focuses on predictive analysis to detect potential threats before they occur. The system improves security and response time in dynamic environments. However, it is mainly designed for specific network architectures and may need adaptation for general systems.

[4] R. Kumar Sharma and S. Singh, *"Machine Learning-Based Cyber Threat Detection and Prevention Systems,"* in IEEE Access, vol. 13, pp. 11234–11250, 2025. This study presents a comprehensive machine learning-based framework for detecting and preventing cyber threats. It highlights the use of supervised learning algorithms for identifying malicious patterns in network traffic. The system improves detection accuracy and reduces false positives. However, it primarily focuses on known attack patterns and lacks adaptability to evolving threats.

[5] L. Wang, H. Chen and Y. Zhang, *"Deep Learning Approaches for Cyber Security Threat Analysis,"* in IEEE Transactions on Information Forensics and Security, vol. 20, pp. 2210–2223, 2025. This paper explores deep learning models for analyzing complex cyber security threats. It utilizes neural networks to identify hidden patterns in large datasets. The approach improves detection of sophisticated attacks and enhances prediction capability. However, it requires high computational resources and large training data.

[6] S. Rao Chinthalpudi, *"A Secured Examination and Identification of Fraudulent URLs in Emails Through Utilization of Machine-Learning Techniques,"* in LNNS, vol. 1357, pp. 689–698, Oct. 2025. This research focuses on detecting fraudulent URLs in email communications using machine learning techniques. It applies feature extraction and classification methods to identify malicious links. The system enhances email security and reduces phishing risks. However, it depends heavily on feature selection and training data quality.

[7] C. Syamsundar, *"A Significant and Enhanced Machine Learning Algorithm Using Feature Selection for Network Intrusion Identification and Detection,"* ICDICI Conference, 2025. This study proposes an improved intrusion detection system using feature selection techniques combined with machine learning algorithms. It reduces computational complexity and improves accuracy. The model efficiently identifies network intrusions.

[8] C. N. Ravi and T. S. Suhasini, *"A Technical Approach for Big Data Analytics to Detect Cyber Crime Using FNN and RNN,"* in LNNS, vol. 1230, pp. 362–371, 2025. This paper introduces a big data-based approach for detecting cybercrime using feedforward and recurrent neural networks. It processes large-scale data efficiently and identifies hidden attack patterns. The model improves predictive performance. However, it requires high computational resources and complex infrastructure.

[9] Shankar Nayak Bhukya, *"Anomalization-based GRU and LSTM Classifiers: An Analyzation of Intelligent Intrusion Detection,"* Scopus Conference, 2025. This work presents an anomaly-based intrusion detection system using GRU and LSTM models. It captures temporal patterns in network data to improve detection accuracy. The system is effective in identifying unknown attacks. However, it may suffer from longer training time and data imbalance issues.

[10] M. Ali, K. Ahmad and F. Hussain, *"An Intelligent Intrusion Detection System Using Machine Learning Techniques,"* in IEEE Access, vol. 13, pp. 14567–14580, 2025. This paper proposes an intelligent intrusion detection system using machine learning algorithms. It enhances detection accuracy by analyzing network traffic behavior. This also reduces false positives and improves reliability. However, it requires continuous updates to handle threats.

[11] S. Gupta and P. Verma, *"Hybrid Machine Learning Models for Cyber Attack Detection,"* in IEEE Transactions on Cybernetics, vol. 55, no. 3, pp. 345–356, 2025. This study introduces hybrid machine learning models for detecting cyber attacks. It combines multiple algorithms to improve classification performance and accuracy. The system achieves better detection results compared to individual models. However, increased complexity may affect implementation and scalability.

Focused Area / Title	Key Findings	Reference
ML Based Cyber Threat Detection [1]	Uses machine learning algorithms to detect cyber threats and analyze network behavior. Improves detection accuracy and reduces false positives but depends on training data quality.	D. Bala et al., "Machine Learning Algorithms for Early Detection of Cybersecurity Threats," JETIR, 2026.
Optimization algorithms help in detecting adversarial attacks in network environments.[2]	To enhance the detection of adversarial and hidden attack patterns in wireless network environments by applying optimization techniques, improving system robustness and resistance against complex cyber threats.	Madhavi Pingili & B. Revathi, "Optimal Foraging Algorithm for Adversarial Inversion Attacks," 2026.
Real-time intrusion detection systems improve predictive threat analysis. [3]	To develop a real-time intrusion detection framework that can continuously monitor network activities and predict potential threats in advance, enabling faster response and improved cyber defense mechanisms.	V. Chaudhary et al., "Real-Time Intrusion Detection System," SAE, 2026.
ML-based systems improve detection accuracy of cyber threats in networks. [4]	To create an efficient cyber threat detection system using supervised machine learning techniques that can accurately classify malicious and normal activities in network traffic.	Sharma & Singh, "Cyber Threat Detection Systems," IEEE Access, 2025.
Deep learning models effectively analyze large-scale cyber security data. [5]	To utilize deep learning techniques for analyzing complex and large-scale cybersecurity datasets, enabling the detection of sophisticated and evolving cyber threats.	L. Wang et al., "Deep Learning for Cyber Security," IEEE TIFS, 2025.
Feature extraction techniques help detect fraudulent URLs and phishing attacks. [6]	To develop systems that can identify fraudulent URLs and phishing attempts by extracting relevant features from web links and applying classification techniques for improved email and web security.	S. Rao Chinthalpudi, "Fraudulent URL Detection," LNNS, 2025.

Focused Area / Title	Key Findings	Reference
Feature selection reduces complexity and improves intrusion detection performance. [7]	To improve intrusion detection efficiency by selecting relevant features from large datasets, reducing computational complexity while maintaining high detection accuracy.	C. Syamsundar, "Feature Selection for IDS," 2025.
Big data analytics improves cybercrime detection using neural networks. [8]	To apply big data analytics and deep learning models such as FNN and RNN to process large volumes of data and identify hidden patterns associated with cybercrime activities.	Ravi & Suhasini, "Cyber Crime Detection," LNNS, 2025.
GRU and LSTM models improve anomaly detection in network traffic. [9]	To design advanced intrusion detection systems using recurrent neural networks that can capture temporal dependencies and detect unknown cyber threats effectively.	S. N. Bhukya, "GRU & LSTM IDS," 2025
ML-based intrusion detection improves accuracy and reduces false alarms. [10]	To enhance the performance of intrusion detection systems by applying machine learning techniques that improve classification accuracy and minimize false positives.	M. Ali et al., "Intelligent IDS," IEEE Access, 2025.
Hybrid ML models increase classification accuracy for cyber attack detection. [11]	To combine multiple machine learning algorithms into a hybrid model that improves prediction performance and enhances the detection of diverse cyber attacks.	S. Gupta & P. Verma, "Hybrid ML Models," IEEE Trans., 2025.

Table 2.1 Literature Survey

3. SOFTWARE REQUIREMNET ANALYSIS

3.1 Modules and Their Functionalities

3.1.1. Data Input

This module is responsible for collecting and loading datasets related to cyberattacks such as SQL Injection, XSS, and malicious URLs. It accepts both normal and malicious data required for training and testing. The data is stored in a structured format for further processing. This module acts as the starting point of the system.

3.1.2. Data Categorization

In this module, the input data is divided into different categories such as normal and malicious. Malicious data is further classified based on attack type. This helps in organizing the data for better analysis. Proper categorization improves the learning capability of the system.

3.1.3. Feature Engineering

This module extracts important features from the dataset such as query patterns, script structures, and URL characteristics. It selects only relevant features to reduce complexity. Feature selection improves model accuracy and efficiency. This step plays a key role in preparing data for training.

3.1.4. Model Training

This module is responsible for training machine learning models using the processed data. Different algorithms are applied to learn patterns of cyberattacks. The models are trained to classify inputs as normal or malicious. Proper training ensures better prediction results.

3.1.5. Model Storage

After training, the models are stored in the system for future use. This avoids retraining every time new input is given. Stored models can be quickly accessed for prediction. This improves system efficiency and reduces processing time.

3.1.6. Input Processing

This module handles real-time user inputs such as queries, scripts, or URLs. The input is processed in the same way as training data. This ensures consistency in prediction. The module prepares input for analysis by the trained models.

3.1.7. Prediction

The trained models analyze the processed input and predict whether it is safe or malicious. The prediction is based on learned patterns. This module is responsible for detecting cyber threats. Accurate prediction is essential for system performance.

3.1.8. Output

This module displays the result of the prediction. It shows whether the input is normal or represents a cyberattack. The output is presented in a simple and understandable format. This helps users take necessary action.

3.1.9. Performance Evaluation

This module evaluates the system performance using testing data. Metrics such as accuracy are used to check model efficiency. It helps in identifying areas for improvement. Regular evaluation ensures reliable system performance.

3.2 Functional Requirements

The functional requirements describe the main operations performed by the system to achieve its objective of detecting cyber security threats. These requirements define how the system accepts input, processes the data, and generates accurate results. They ensure that the system operates efficiently, provides reliable outputs, and supports real-time threat detection. The system is designed to handle different types of inputs such as SQL queries, scripts, and URLs, and process them using machine learning techniques to identify potential attacks.

- The system shall accept user inputs such as SQL queries, scripts, and URLs and route them to the processing module.
- The system shall validate the input to ensure it is not empty and is in the correct format before processing.
- The system shall perform preprocessing operations such as cleaning, normalization, and formatting of input data.
- The system shall extract relevant features from the processed data for analysis.
- The system shall apply machine learning algorithms to classify the input as malicious or benign.

3.3 Non – Functional Requirements

Non-functional requirements describe the quality attributes and performance expectations that govern how the system operates. Rather than defining specific features, they specify how the system

should behave under various conditions and how efficiently it should deliver results. These requirements ensure reliability, usability, scalability, and overall consistency throughout the system's operation and future maintenance. The following points summarize the key non-functional characteristics implemented in the system.

- The system shall ensure high reliability and stability during all stages of text processing and classification.
- The system shall support scalable performance as dataset size and category complexity increase.
- The system shall maintain efficient processing with minimal latency in generating predictions.
- The system shall preserve data privacy and confidentiality for all user-generated inputs processed by the framework.

3.4 Feasibility Study

The feasibility study is carried out to evaluate whether the proposed system can be developed and implemented effectively in a real-world environment. It helps in understanding whether the system is practical, efficient, and suitable based on available resources and requirements. This analysis ensures that the project can function properly without creating unnecessary burden. The system is designed to handle cyber threat detection using machine learning techniques while maintaining good performance with limited computational resources. It is capable of processing large datasets related to attacks such as SQL Injection, XSS, and malicious URLs in an efficient manner, making it suitable for real-time applications. The study also focuses on the smooth integration of different modules such as data processing, model training, and prediction. This analysis ensures that the project can function properly without creating unnecessary burden. The system follows a clear workflow, which reduces complexity and improves performance.

Three key considerations involved in the feasibility analysis are,

- Economic Feasibility
- Technical Feasibility
- Social Feasibility

3.4.1 Economic Feasibility

The economical feasibility study is conducted to evaluate the cost required for developing and implementing the proposed system. The system is designed using open-source technologies such as Python and machine learning libraries, which significantly reduces the overall development cost. There is no need for expensive licensed software or specialized tools, making the project cost-

effective. The hardware requirements are also minimal, as the system can run on standard computers without requiring high-end configurations.

The maintenance and operational costs of the system are low, as updates and improvements can be made easily without additional investment. By detecting and preventing cyberattacks such as SQL Injection, XSS, and malicious URLs, the system helps in reducing financial losses caused by security breaches. This makes the project beneficial for organizations and individuals. Considering the low cost and high benefits, the proposed system is economically feasible.

The cyber security threat detection system is economically feasible as it primarily relies on widely available and low-cost technologies such as Python, Flask, and MySQL, which are either open-source or require minimal investment. The hardware requirements are also basic, ensuring that the system can be developed and deployed without the need for expensive infrastructure. It also prevents potential financial losses caused by cyberattacks such as data breaches and system downtime.

3.4.2 Technical Feasibility

The technical feasibility study evaluates whether the proposed system can be developed and implemented using the available technologies and resources. The system is built using widely used technologies such as Python, machine learning algorithms, and basic web development tools, which are easy to implement and well supported. These technologies do not require complex infrastructure and can be handled with standard development environments.

The system is also scalable and can handle increasing data and additional features if required. It can be updated with new datasets to improve performance and adapt to new cyber threats. Since the system can be developed, deployed, and maintained using available tools and resources without technical constraints, it is considered technically feasible.

3.4.3 Social Feasibility

The social feasibility study focuses on the acceptance and usability of the proposed system among users. The system is designed to be simple and easy to use, so users can interact with it without requiring advanced technical knowledge. The interface and workflow are kept straightforward, allowing users to provide input and understand the output without difficulty.

The system helps in identifying cyber threats such as SQL Injection, XSS, and malicious URLs, which increases user confidence in maintaining security. It protects sensitive data and reduces the risk of cyberattacks, making it beneficial for both individuals and organizations. The system also promotes awareness about cyber security by helping users understand different types of threats.

4. SYSTEM SPECIFICATIONS

4.1 Software Requirements

The software requirements define the technologies and tools used for developing and implementing the proposed cyber security system. The system is designed using a machine learning-based approach, which requires a suitable programming environment, development tools, and frameworks to ensure efficient processing and accurate threat detection. The system is developed using Python due to its simplicity and strong support for machine learning and data analysis. A web-based interface is created to allow users to interact with the system easily, while backend processing is handled using lightweight frameworks.

The front-end of the system is designed using standard web technologies such as HTML, CSS, and JavaScript to provide a simple and user-friendly interface. The backend is implemented using the Flask framework, which handles user requests, processes input data, and returns prediction results. The system uses a relational database to store data and results efficiently. Overall, the selected software components ensure flexibility, scalability, and efficient execution of the system.

Software Specifications

- **Operating System**: Windows 7 Ultimate
- **Coding Language**: Python
- **Front-End**: HTML, CSS, JavaScript
- **Back End**: Flask
- **Designing Tools**: HTML, CSS, JavaScript
- **Database**: MySQL (WAMP Server)

4.2 Hardware Requirements

The hardware requirements specify the physical components needed to develop and run the proposed cyber security system efficiently. Since the system involves machine learning-based analysis and processing of input data, it requires a system with adequate processing capability and memory support. The hardware should be capable of handling data preprocessing, feature extraction, and model execution without performance issues. A standard computer system is sufficient for development and testing, while higher configurations can further improve performance and speed.

The system does not require highly advanced hardware, but a stable configuration is necessary to ensure smooth execution of machine learning algorithms and web-based operations. Input and output devices such as keyboard, mouse, and monitor are required for user interaction, while sufficient storage is needed to manage datasets and system files.

In addition to the basic configuration, the performance of the system can be significantly improved by using upgraded hardware components. Machine learning operations such as data preprocessing, model training, and prediction may consume more memory and processing power when working with larger datasets. Therefore, using a system with a higher RAM capacity and a modern multi-core processor can enhance speed and efficiency. A stable internet connection is also beneficial for accessing datasets, updating libraries, and deploying the application if required. Although the system can run on minimum specifications.

Hardware Specifications

- **Processor**: Pentium – IV
- **RAM**: 4 GB (minimum)
- **Hard Disk**: 20 GB
- **Keyboard**: Standard Windows Keyboard
- **Mouse**: Two or Three Button Mouse
- **Monitor**: SVGA Monitor

5. SYSTEM ARCHITECTURE

5.1 System Architecture

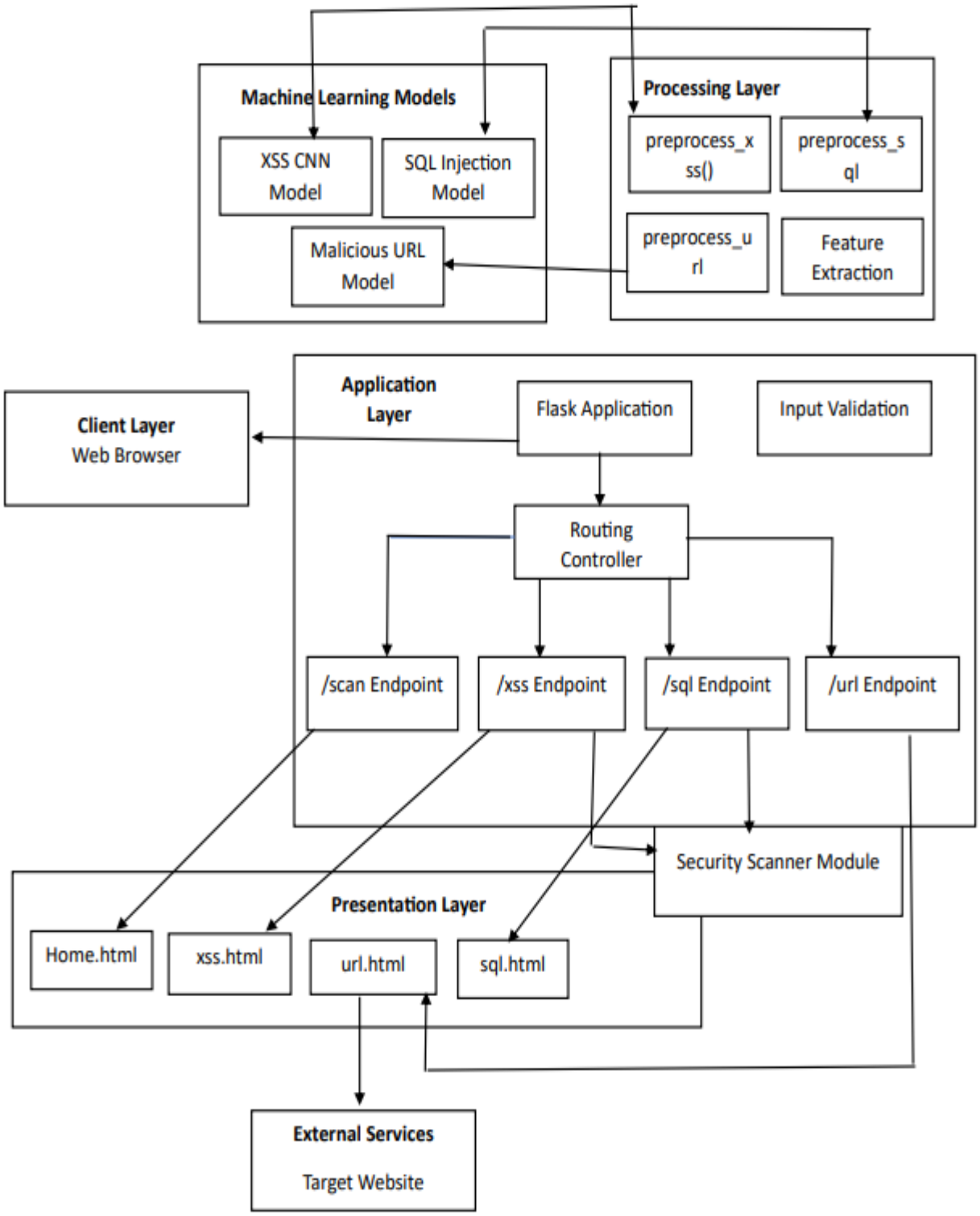


Fig. 5.1 System Architecture

The system architecture of the cyber security threat detection system is designed as a layered and modular framework to ensure efficient processing, scalability, and maintainability. The architecture consists of multiple layers, including the client layer, application layer, processing layer, machine learning model layer, presentation layer, and external services, each performing a specific role in the overall workflow.

At the top level, the client layer represents the user interface through which users interact with the system using a web browser. Users provide inputs such as SQL queries, scripts, or URLs, which are then sent to the application layer for further processing. This layer acts as the entry point of the system.

The application layer is the core component of the system, implemented using a Flask application. It handles request routing, input validation, and communication between different modules. The routing controller directs user requests to specific endpoints such as scan, xss, sql, and url, depending on the type of input provided. This ensures that each type of cyber threat is processed through the appropriate pipeline.

The processing layer is responsible for preparing the input data for analysis. It includes modules for preprocessing different types of inputs such as XSS scripts, SQL queries, and URLs. This layer performs tasks like cleaning, normalization, and feature extraction, converting raw input into structured data suitable for machine learning models.

The machine learning model layer consists of specialized models designed to detect different types of cyber threats. These include the XSS CNN model, SQL Injection detection model, and Malicious URL detection model. Each model is trained to identify patterns specific to its domain, improving detection accuracy and system performance.

The presentation layer manages the user interface and displays the results. It includes web pages such as home.html, xss.html, sql.html, and url.html, which present the detection results in a clear and user-friendly format. This layer ensures effective communication of results to the end user.

Overall, the system architecture follows a structured and modular design that enables efficient data flow from input to output. By separating functionalities into distinct layers, the system achieves better scalability, easier maintenance, and improving performance.

Additionally, the architecture supports seamless integration with external services such as threat intelligence APIs and security databases to enhance detection capabilities with real-time updates.

5.2 Data Flow Diagram

The Data Flow Diagram (DFD) represents how data moves through the system and how it is processed at different stages. It shows the flow of input data from the user to various processing modules and finally to the output. The main components of the DFD include external entities, processes, and data stores, which together describe the working of the system.

At the initial stage, the user provides input in the form of SQL queries, scripts, or URLs. This input is received by the system and passed to the preprocessing module, where the data is cleaned, normalized, and formatted. After preprocessing, the data moves to the feature extraction process, where important attributes are identified and converted into a suitable format for analysis.

The processed data is then sent to the machine learning models, where classification is performed to detect whether the input is malicious or benign. Based on the analysis, the system generates the output indicating the type of attack detected or whether the input is safe. The result is then displayed to the user in a clear and understandable format.

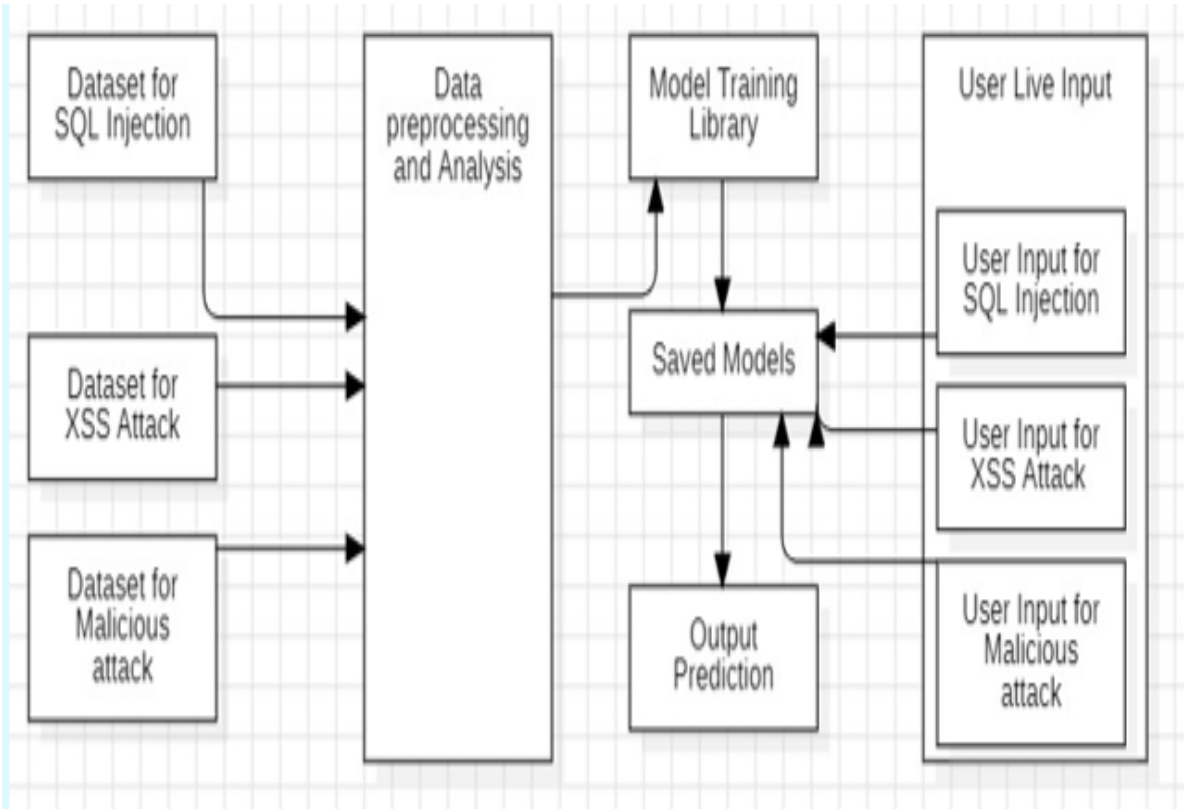


Fig 5.2: Dataflow Diagram

5.3 UML DIAGRAMS

UML (Unified Modeling Language) is a standardized language used for specifying, visualizing, constructing, and documenting the artifacts of software systems. UML helps in representing the design of systems and understanding their components. Created by the Object Management Group (OMG), UML 1.0 was proposed in January 1997. UML is closely associated with object-oriented analysis and design. The two main categories of UML diagrams are Behavioral and Structural diagrams, each serving distinct purposes in the modeling process.

UML is closely associated with object-oriented analysis and design, making it especially useful for systems that are developed using modular and reusable software principles. It allows developers to describe both the structure and behaviour of a system before actual coding begins, thereby reducing design errors and improving software quality.

The Behavioral UML diagrams describe the behavior of the system, its actors, and the interaction between the components. On the other hand, Structural UML diagrams depict the static structure of the system, showing its components and relationships. UML has been integrated as a standard by OMG, and its primary goals are to provide a formal basis for understanding modeling languages, offer a ready to use expressive language for system developers, and encourage the growth of object oriented tools.

Goals of UML:

- To provide a standard visual representation of the system design.
- To simplify understanding of system architecture for developers and reviewers.
- To improve communication among team members during development.
- To model both structural and behavioral aspects of the system.
- To support object-oriented design and development practices.
- To document the system clearly for future reference and maintenance.
- To reduce system complexity through diagrammatic representation.
- To assist in planning and designing before actual implementation.
- To enable easy modification and scalability of the system design.
- To ensure a systematic and organized software development process.

The different types are broken down as follows:

1. Use case Diagram

2. Class Diagram
3. Sequence diagram
4. Activity Diagram

5.3.1 USE CASE DIAGRAM

The Use Case Diagram illustrates the interaction between external actors and the Cyber Security Threat Detection System, providing a clear understanding of how the system operates and how users engage with its functionalities. It represents the overall workflow of the system, starting from user input to the final prediction output. This diagram helps in identifying the major system functionalities and their relationships with different actors, making it easier to understand system behavior at a high level.

In this system, the primary actor is the User, who interacts with the application by providing various types of inputs such as SQL queries, scripts, and URLs. These inputs may contain potential cyber threats like SQL Injection, Cross-Site Scripting (XSS), or malicious links. The system acts as an intelligent processing unit that analyzes these inputs using machine learning techniques and provides accurate predictions. Another implicit actor is the System Backend (Admin role), which manages model execution, data processing, and overall system performance.

The use case diagram plays an important role in visualizing how different components of the system are interconnected. It clearly shows how user actions trigger system processes such as input handling, preprocessing, model loading, and prediction generation. This structured representation improves system design clarity and helps in identifying possible improvements or extensions in future development.

The process begins when the user provides live input to the system. The system then processes this input through multiple stages, including cleaning, normalization, and feature extraction. After preprocessing, the system loads the appropriate machine learning models that are trained to detect different types of cyber threats. The processed data is passed to these models for analysis, and the system generates a prediction based on learned patterns. Finally, the output is displayed to the user, indicating whether the input is malicious or safe.

The proposed system is primarily used for detecting and preventing cyber security threats in web-based applications and network environments. In this use case, a user (such as a system administrator or security analyst) submits input data like SQL queries, URLs, or script code through the web interface. The system processes this input and analyzes it using machine learning models to determine whether it is normal or malicious. Based on the analysis, the system classifies the input into different categories such as SQL Injection, Cross-Site Scripting (XSS), or Malicious URL attacks.

Components of the Use Case Diagram

User:

The user interacts with the system by providing input such as SQL queries, scripts, or URLs. The user can request analysis and view the prediction results to determine whether the input is safe or harmful.

System / Admin:

The system (or admin role) is responsible for processing inputs, managing machine learning models, and generating accurate predictions. It ensures proper functioning of all modules and maintains system performance.

Use Live Input:

This use case allows the user to enter real-time input data into the system. The input can be in different formats such as queries, scripts, or URLs, which are analyzed for potential threats.

Processing of Attacks:

The system processes the given input by performing preprocessing steps such as cleaning, normalization, and feature extraction. This prepares the data for machine learning analysis.

Loading Models:

The system loads the trained machine learning models required for classification. These models analyze the processed input and identify patterns related to cyber threats.

Output Prediction:

The system generates prediction results based on the analysis. It classifies the input as malicious or benign depending on the detected patterns.

Output to End Users:

The final result is displayed to the user in a clear and understandable format. The output indicates whether an attack is detected or if the input is safe.

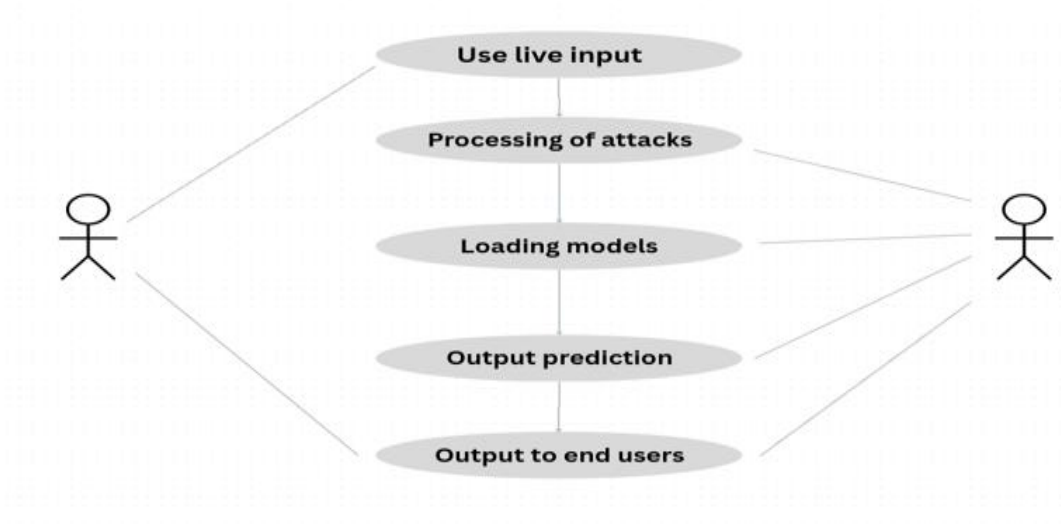


Fig 5.3.1 Use Case diagram

5.3.2. CLASS DIAGRAM

The Class Diagram represents the structural design of the Cyber Security Threat Detection System by illustrating the classes, their attributes, methods, and the relationships between them. It provides a static view of the system and helps in understanding how different components are organized and interact internally. This diagram plays an important role in defining the architecture of the system and guiding the implementation process.

In this system, the main classes include the System class and the User class, which are interconnected to perform various operations such as input handling, preprocessing, model execution, and prediction generation. The diagram shows how the user interacts with the system by providing inputs and how the system processes these inputs using machine learning techniques to detect cyber threats.

The System class acts as the core component that manages the machine learning models and performs key operations such as preprocessing, model saving, and prediction. It contains attributes and methods required for handling data and executing models efficiently. This class is responsible for ensuring that the input data is properly processed and analyzed.

The User class represents the interaction between the user and the system. It includes different types of inputs such as malicious URL detection, SQL injection detection, and XSS attack detection. The class also includes methods that handle dataset preprocessing, model training and testing, user input handling, model loading, prediction generation, and output display. This class acts as a bridge between the user and the system functionality.

The relationship between the User class and the System class is shown through an association, where the user interacts with the system to perform operations. The user provides input data, and the system processes this data and returns the results. This interaction ensures smooth execution of the system workflow.

Overall, the class diagram provides a clear representation of the internal structure of the system, highlighting how different components are organized and how they collaborate to achieve the objective of detecting cyber threats. It helps in improving system design, maintainability, and scalability.

Components of the Class Diagram

System Class:

This class handles all core functionalities related to machine learning operations. It includes attributes such as models and methods like preprocessing(), saving_models(), and predictions(). It is responsible for managing trained models and performing analysis on input data.

User Class:

This class represents the user interaction with the system. It accepts inputs related to malicious attack detection, SQL injection detection, and XSS attack detection. It includes methods such as dataset preprocessing(), model training and testing(), user input(), loading training model(), predictions(), and output display().

Relationship:

The User class is associated with the System class, where the user sends input data to the system, and the system processes the data using machine learning models to generate output. This relationship ensures proper communication between user actions and system responses.

Preprocessing Module

The Preprocessing Module is responsible for preparing raw input data before it is passed to the machine learning models. It handles tasks such as removing unwanted characters, normalizing text, tokenization, and handling special symbols present in SQL queries, scripts, and URLs. This module ensures that the input data is converted into a clean and structured format suitable for analysis. By improving data quality, preprocessing enhances model performance and increases the accuracy of threat detection. It plays a crucial role in reducing noise and ensuring consistency across different types of inputs.

Feature Extraction Module

The Feature Extraction Module transforms the preprocessed data into meaningful numerical representations that can be understood by machine learning algorithms. It extracts important patterns and characteristics from the input data, such as keyword frequency, suspicious patterns, and structural features. Techniques such as vectorization and encoding are used to convert textual input into feature vectors. This module is essential for improving the efficiency and accuracy of the classification process, as it helps the model focus on relevant information while ignoring unnecessary details.

Machine Learning Model Module

The Machine Learning Model Module is the core component responsible for analyzing input data and detecting cyber threats. It includes trained models such as Decision Tree, Random Forest, and Support

Vector Machine, which are used to classify inputs as malicious or benign. The models are trained using historical datasets and are capable of identifying patterns associated with different types of attacks. This module continuously processes incoming data and generates predictions, making it a key component for intelligent threat detection.

Model Training and Testing Module

The Model Training and Testing Module is responsible for building and evaluating machine learning models using training datasets. It splits the dataset into training and testing sets, applies algorithms, and evaluates model performance using metrics such as accuracy and precision. This module ensures that the models are reliable and capable of handling real-world data. It also helps in selecting the best-performing model for deployment, thereby improving overall system efficiency.

Input Handling Module

The Input Handling Module manages user inputs provided through the web interface. It accepts different types of data such as SQL queries, scripts, and URLs, and ensures that the input is properly captured and validated before processing. This module checks for invalid or empty inputs and ensures smooth data flow into the system. It acts as the entry point of the system and plays an important role in maintaining system stability and usability.

Prediction Module

The Prediction Module generates the final output based on the analysis performed by the machine learning models. It processes the feature vectors and classifies the input as malicious or benign. It also identifies the type of attack, such as SQL Injection or XSS, if detected. This module ensures that predictions are generated quickly and accurately, enabling real-time threat detection and response.

Output Display Module

The Output Display Module presents the results of the prediction to the user in a clear and understandable format. It displays messages such as “Attack Detected” or “Benign Input,” along with visual indicators for better readability. This module ensures that users can easily interpret the results and take necessary actions. It enhances user experience by providing immediate and meaningful feedback.

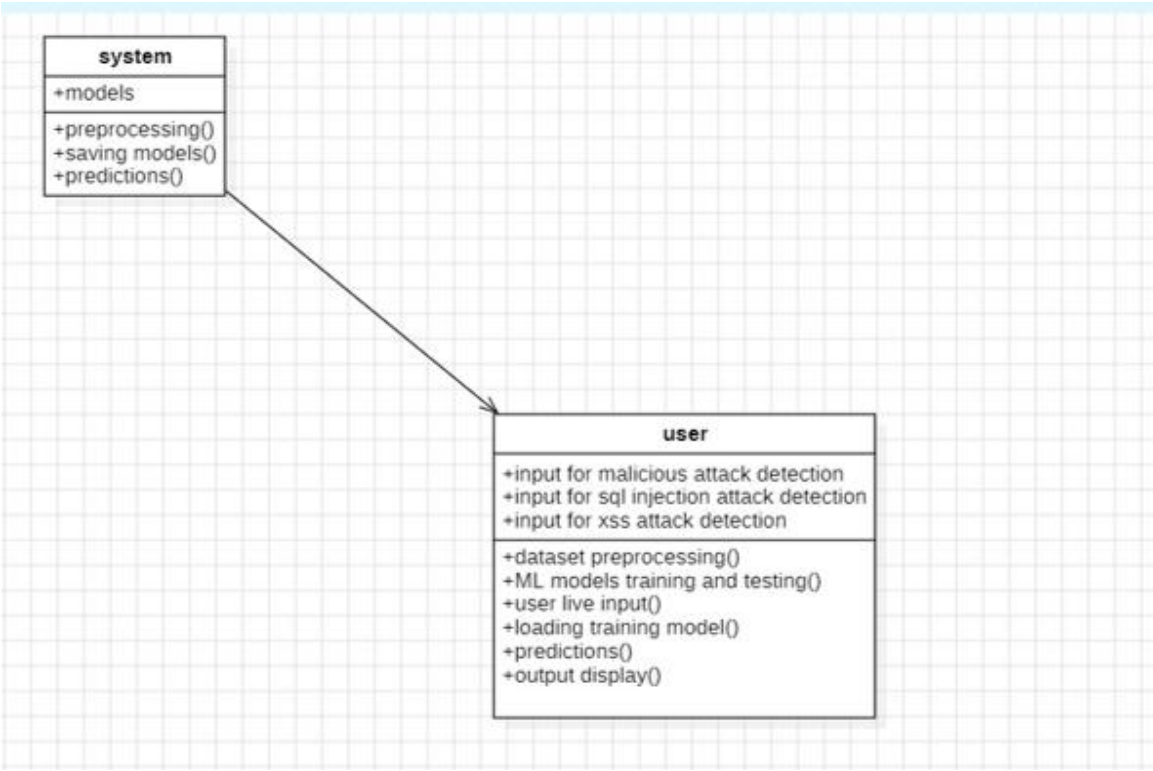


Fig 5.3.2 Class diagram

5.3.3. SEQUENCE DIAGRAM

The Sequence Diagram illustrates the dynamic interaction between different components of the Cyber Security Threat Detection System. It represents how data flows step-by-step from the user input stage to the final prediction output. This diagram helps in understanding the execution flow, communication between modules, and the order in which operations are performed within the system. It mainly involves components such as Data Collection, Preprocessing, Trained Model, Model, and System.

The process begins with the user providing input in the form of SQL queries, scripts, or URLs. These inputs may contain malicious patterns or normal data, and they are first captured by the Data Collection module. This module acts as the entry point of the system, ensuring that user input is received properly and forwarded for further processing.

Once the input is collected, it is passed to the Preprocessing module. In this stage, the system performs several operations such as removing unwanted characters, normalizing text, handling encoded values, and converting the input into a structured format. This step is crucial because raw input data is often noisy and inconsistent. Preprocessing ensures that the data becomes clean and suitable for machine learning analysis. After successful preprocessing, the system confirms that the data is ready for the next stage.

The processed data is then sent to the Trained Model module. This module checks whether a trained machine learning model is already available. If a trained model exists, the system directly proceeds to prediction. Otherwise, the Model module initiates the training and testing process. During this stage, historical datasets are used to train machine learning algorithms, and the model is evaluated for accuracy and performance.

After training is completed, the system validates the model to ensure that it meets the required performance standards. Once validated, the trained model is saved within the system. This step ensures that the model does not need to be retrained repeatedly, thereby improving system efficiency and reducing processing time for future inputs.

Following the model preparation, the system is ready to handle live user inputs. The user provides real-time input, which is processed using the trained model. The model analyzes the input data, extracts relevant patterns, and classifies it as either malicious or benign. If the input contains attack patterns such as SQL Injection, XSS, or malicious URLs, the system identifies the type of attack and flags it accordingly.

Finally, the system generates the predicted output and displays it to the user. The output clearly indicates whether the input is safe or harmful. This real-time prediction helps users take immediate action to prevent potential security threats.

Sequence Steps

User Data Input

The sequence starts when the user provides input data such as a URL, SQL query, or script through the web interface. This input may contain malicious or normal content, and it is captured by the Data Collection module for further processing.

Submission Successful

After receiving the input, the system confirms that the data has been successfully submitted. This ensures that the input is properly recorded and ready for processing.

Pre-processed Input

The input is forwarded to the Preprocessing module, where various cleaning and transformation operations are performed. The data is converted into a structured format suitable for machine learning models.

Preprocessing Successful

Once preprocessing is completed, the system confirms that the input data is clean and ready for analysis. This step ensures data consistency and reliability.

Model Training and Testing

If a trained model is not already available, the system initiates the training process. Machine learning algorithms are applied to historical data, and the model is tested to evaluate its performance and accuracy.

Trained Successfully

After training and testing, the system confirms that the model has been successfully trained and is ready for use in prediction.

Save Model

The trained model is stored in the system so that it can be reused for future predictions without retraining.

Saving Successful

The system verifies that the model has been saved correctly, ensuring availability for real-time operations.

User Live Input

The user provides real-time input, which is processed using the trained model. This step represents the actual working phase of the system.

Predicted Output

The system analyzes the input and generates the final output, classifying it as malicious or benign. The result is displayed to the user for further action.

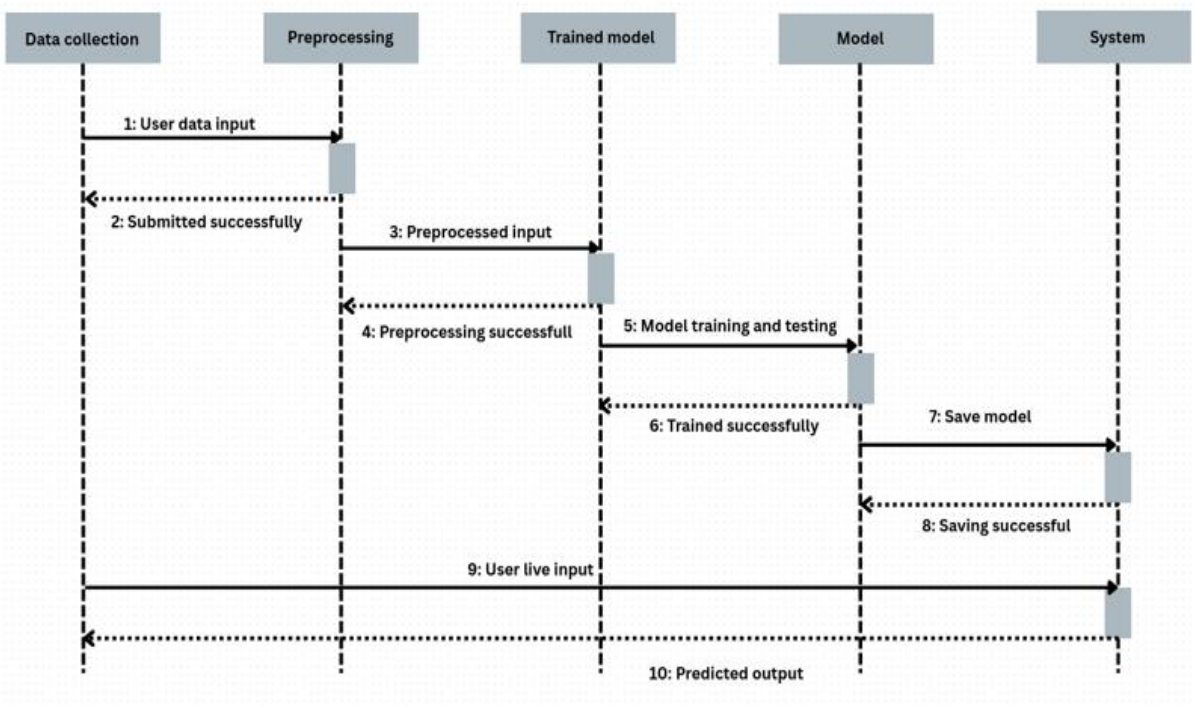


Fig 5.3.3 Sequence diagram

5.3.4. ACTIVITY DIAGRAM

The Activity Diagram represents the workflow of the Cyber Security Threat Detection System, illustrating how different activities are performed sequentially from input to output. It provides a clear understanding of the operational flow of the system and highlights how data is processed at each stage. This diagram focuses on the flow of control between different actions such as user input, data processing, prediction, and result generation.

The process begins with the initial node, which indicates the start of the system operation. The first activity is the User Live Input, where the user provides input data such as SQL queries, scripts, or URLs through the interface. This input may contain either normal or malicious content and serves as the primary data for analysis.

Once the input is received, the system moves to the Processing of Input Data stage. In this phase, the input undergoes preprocessing operations such as cleaning, normalization, and formatting. Special characters, unnecessary symbols, and noise are removed to ensure that the data is structured properly. This step is essential to prepare the input for accurate analysis by machine learning models.

After preprocessing, the system proceeds to the Loading Prediction stage. In this step, the trained machine learning model is loaded into the system memory. This ensures that the system is ready to analyze the input data using previously learned patterns and features. If the model is already available, it is directly used without retraining, which improves efficiency and reduces processing time.

The next step is Output Prediction, where the system applies the machine learning model to the processed input data. The model analyzes the data and determines whether it contains any cyber threats such as SQL Injection, Cross-Site Scripting (XSS), or malicious URLs. Based on the analysis, the system classifies the input as either malicious or benign.

Following prediction, the system moves to the Output to End User stage. In this step, the final result is displayed to the user in a clear and understandable format. The output indicates whether an attack is detected or if the input is safe. Visual indicators such as colors or labels may also be used to enhance clarity and user experience.

The activity diagram also represents the logical sequence and control flow of operations within the system, highlighting how different actions are connected from start to end. It illustrates the decision-making points where the system evaluates conditions, such as determining whether the input is malicious or benign based on the model prediction.

The diagram shows how the flow branches depending on the result and then converges back to deliver the final output to the user. It also emphasizes the continuous nature of the system, where after completing one cycle, the system is ready to process new inputs. By clearly mapping each step and transition, the activity diagram helps in understanding system behavior, identifying potential bottlenecks, and ensuring that the workflow is efficient, structured, and logically consistent.

Finally, the process reaches the end node, indicating the completion of the workflow. The system is then ready to accept new inputs and repeat the process.

Flow of Activities

Start Node

The activity begins at the start node, which represents the initiation of the system process. This stage indicates that the system is ready to receive input from the user. It acts as the entry point of the workflow and ensures that all necessary system components are initialized before processing begins. The start node does not perform any operation but signifies the beginning of the sequence of activities in the system.

User Live Input

In this stage, the user interacts with the system by providing input data through the web interface. The input may include SQL queries, JavaScript code, or URLs that need to be analyzed for potential security threats. Since the system is designed to handle real-time data, this input can vary in format and complexity. The user input acts as the primary data source for the entire process, and its correctness directly affects the system's performance.

Processing of Input Data

Once the input is received, the system proceeds to process the data. This stage involves preprocessing techniques such as removing unwanted characters, handling special symbols, normalizing text, and converting the input into a structured format. The system ensures that noisy and unstructured data is cleaned and standardized. This step is critical because machine learning models require properly formatted data for accurate predictions. Any inconsistencies in input data are resolved at this stage to improve reliability.

Loading Prediction Model

After preprocessing, the system loads the trained machine learning model required for analysis. This step ensures that the system has access to previously trained models that contain learned patterns of cyber threats. The model may include classifiers trained to detect SQL Injection, XSS attacks, or malicious URLs. Loading the model into memory allows the system to perform fast and efficient predictions without retraining the model each time.

Output Prediction

In this stage, the processed input data is passed to the machine learning model for analysis. The model examines the data using learned features and patterns to determine whether the input is malicious or benign. It identifies specific attack types if present, such as SQL Injection or XSS. This step is the core functionality of the system, where intelligent decision-making takes place based on data analysis.

Output to End User

After the prediction is generated, the system displays the result to the user. The output clearly indicates whether the input is safe or contains a cyber threat. Messages such as "Attack Detected" or "Benign Input" are shown, along with possible visual indicators like color coding. This stage ensures that the user can easily understand the result and take necessary action if a threat is detected.

End Node

The activity concludes at the end node, which represents the completion of the process. At this point, the system has successfully processed the input and delivered the output. The system
then returns to an idle state, ready to accept new input and repeat the process. This ensures continuous operation and real-time threat detection capability.

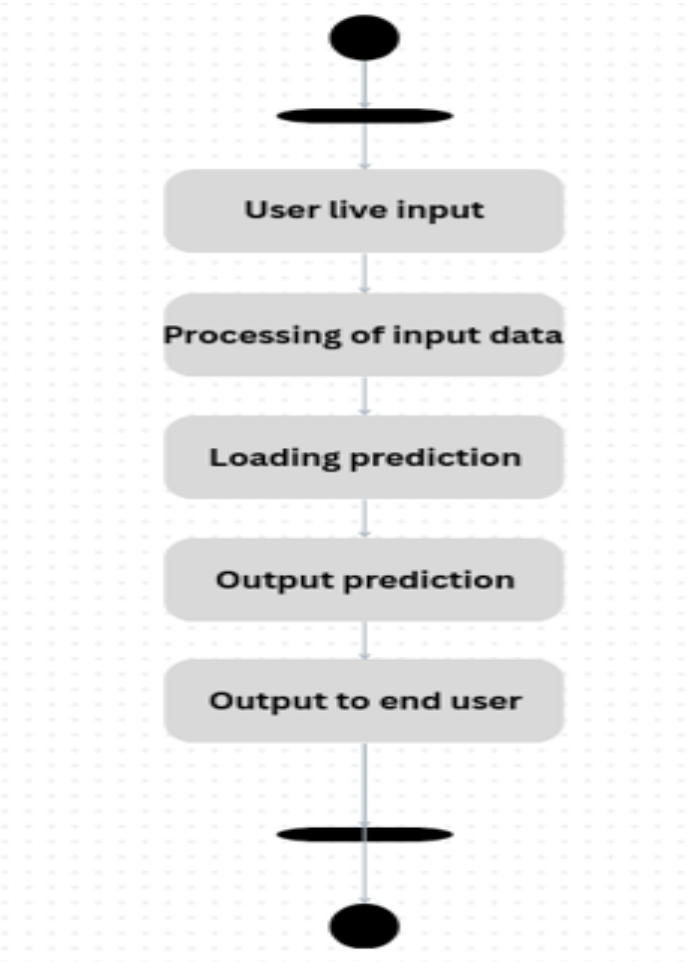


Fig 5.3.4 Activity diagram

6. IMPLEMENTATION AND CODING

6.1 Implementation

6.1.1 Python

Python is a high-level, interpreted, object-oriented, and general-purpose programming language used for the development of the proposed system. It is widely known for its simplicity and readability, which allows developers to write clean and understandable code. Python uses indentation instead of brackets, which makes the structure of the code more clear and organized. This feature makes it easier to debug and maintain the system.

In this project, Python is used as the main programming language to implement all functionalities such as data handling, preprocessing, feature extraction, model training, and prediction. It supports multiple programming paradigms including procedural, object-oriented, and functional programming, which helps in designing a flexible and scalable system. The language also provides automatic memory management and dynamic typing, which reduces the complexity of coding.

Python is platform-independent, which means the same code can run on different operating systems without modification. It also has strong community support and continuous updates, making it reliable for long-term use. Python is widely used in industries such as cybersecurity, artificial intelligence, data science, and web development due to its versatility.

Another important feature of Python is its extensive library support. Libraries such as NumPy and Pandas are used for data manipulation, while Scikit-learn is used for implementing machine learning algorithms. These libraries reduce development time and improve efficiency by providing pre-built functions.

Python is also suitable for rapid application development. It allows quick prototyping and testing of ideas, which is useful in machine learning projects where models need to be tested and improved continuously. The simplicity of Python makes it easy to integrate with other technologies and tools.

- Data preprocessing and cleaning
- Feature extraction and selection
- Implementation of machine learning algorithms
- Model training and evaluation
- Real-time prediction of cyber threats
- Integration of different system modules

Advantages of Python

(a) Extensive Libraries:

Python downloads with an extensive library and it contain code for various purposes like regular expressions, Speech Recognition, documentation-generation, unit-testing, web browsers, threading, databases, CGI, email, and more. So, we don't have to write the complete code for that manually.

(b) Extensible:

As we have seen earlier, Python can be extended to other languages. You can write some of your code in languages like C++ or C. This comes in handy, especially in projects.

(c) Embeddable:

Complimentary to extensibility, Python is embeddable as well. You can put your Python code in your source code of a different language, like C++. This lets us add scripting capabilities to our code in the other language.

(d) Improved Productivity:

The language's simplicity and extensive libraries render programmers more productive than languages like Java and C++ do. Also, the fact that you need to write less and get more things done.

(e) IOT Opportunities:

Since Python forms the basis of new platforms like Raspberry Pi, it finds the future bright for the Internet of Things. This is a way to connect the language with the real world

(f) Simple and Easy:

When working with Java, you may have to create a class to print 'Hello World'. But in Python, just a print statement will do. It is also quite easy to learn, understand, and code. This is why when people pick up Python, they have a hard time adjusting to other more verbose languages like Java.

(g) Readable:

Because it is not such a verbose language, reading Python is much like reading English. This is the reason why it is so easy to learn, understand, and code. It also does not need curly braces to define blocks, and indentation is mandatory. These further aids the readability of the code.

(h) Object-Oriented:

This language supports both the procedural and object-oriented programming paradigms. While functions help us with code reusability, classes and objects let us model the real world. A class allows the encapsulation of data and functions into one.

(i) Free and Open-Source:

Like we said earlier, Python is freely available. But not only can you download Python for free, but you can also download its source code, make changes to it, and even distribute it. It downloads with an extensive collection of libraries to help you with your tasks.

(j) Portable:

When you code your project in a language like C++, you may need to make some changes to it if you want to run it on another platform. But it isn't the same with Python. Here, you need to code only once, and you can run it anywhere. This is called Write Once Run Anywhere (WORA).

However, you need to be careful enough not to include any system-dependent features.

(k) Interpreted:

Lastly, we will say that it is an interpreted language. Since statements are executed one by one, debugging is easier than in compiled languages.

Disadvantages of Python

1. Speed Limitations:

We have seen that Python code is executed line by line. But since Python is interpreted, it often results in slow execution. This, however, isn't a problem unless speed is a focal point for the project. In other words, unless high speed is a requirement, the benefits offered by Python are enough to distract us from its speed limitations.

2. Weak in Mobile Computing and Browsers:

While it serves as an excellent server-side language, Python is much rarely seen on the client- side. Besides that, it is rarely ever used to implement smartphone-based applications. One such application is called Carbonnelle.

The reason it is not so famous despite the existence of Brython is that it isn't that secure.

3. Design Restrictions:

As you know, Python is dynamically-typed. This means that you don't need to declare the type of variable while writing the code. It uses duck-typing. While this is easy on the programmers during coding, it can raise run-time errors.

4. Underdeveloped Database Access Layers:

Compared to more widely used technologies like JDBC (Java Data Base Connectivity) and ODBC (Open Data Base Connectivity), Python's database access layers are a bit underdeveloped.

Consequently, it is less often applied in huge enterprises.

5. Slower Execution Speed:

One of the main disadvantages of Python is its slower execution speed compared to compiled languages like C++ or Java. Python is an interpreted language, which means the code is executed line by line instead of being compiled into machine code beforehand. This process increases execution time, especially for large-scale applications or tasks that require high performance.

6. High Memory Consumption:

Python tends to use more memory compared to languages like C or C++. This is because of its flexible data types and dynamic nature. As a result, it may not be the best choice for memory-intensive applications or systems with limited resources.

7. Global Interpreter Lock (GIL) Limitation:

Python has a mechanism called the Global Interpreter Lock (GIL), which allows only one thread to execute at a time in a single process. This limits the performance of multi-threaded programs, especially in CPU-bound tasks, and makes it less efficient for applications that require parallel processing.

6.1.2 MACHINE LEARNING

Machine learning models for speech recognition require a large amount of data for training. This data includes audio samples of different users speaking various phrases and commands that the voice assistant should recognize. But in this project machine learning is playing a role indirectly through the use of two specific libraries: spaCy and the Google Cloud Speech Recognition API. Here, spaCy is used for natural language processing (NLP). The nlp object is an instance of the spaCy language model, specifically the English language model (en_core_web_sm). When you process a text with nlp, it applies various machine learning models to tokenize, parse, and tag the input text. It identifies parts of speech, named entities, and other linguistic features.

The recognize google method sends the recorded audio data to Google's servers, where machine learning models process the audio to transcribe it into text. This involves complex acoustic modeling and language modeling techniques. The Google Cloud Speech Recognition API uses machine learning models to handle various accents, intonations, and spoken language nuances, making it a powerful tool for speech recognition.

Machine Learning (ML) is a branch of artificial intelligence that enables computer systems to learn from data and improve their performance without being explicitly programmed. Instead of

relying on predefined rules, machine learning models analyze patterns within data and make decisions or predictions based on those patterns. This capability makes machine learning highly useful in solving complex problems where traditional programming approaches are not efficient. In the context of cyber security, machine learning plays a crucial role in identifying threats, detecting anomalies, and preventing attacks in real time.

Machine learning works by training models using historical data. During the training phase, the model learns relationships between input features and corresponding outputs. Once trained, the model can be used to predict outcomes for new, unseen data. This process involves several stages, including data collection, preprocessing, feature extraction, model training, evaluation, and deployment. Each stage is important to ensure that the model performs accurately and reliably.

There are three main types of machine learning: supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, the model is trained using labeled data, where both input and output are known. This approach is commonly used for classification and regression tasks. For example, in cyber security, supervised learning can be used to classify inputs as malicious or benign based on labeled datasets. Unsupervised learning, on the other hand, works with unlabeled data and is used to identify hidden patterns or group similar data points. This is useful in detecting unknown or new types of attacks. Reinforcement learning involves training a model through trial and error, where the system learns by receiving rewards or penalties based on its actions.

Data preprocessing is a critical step in machine learning. Raw data is often noisy, inconsistent, or incomplete, which can negatively impact model performance. Therefore, preprocessing techniques such as data cleaning, normalization, tokenization, and handling missing values are applied to improve data quality. In cyber security applications, preprocessing may involve removing special characters, converting text into a standard format, and extracting meaningful features from input data such as SQL queries, scripts, or URLs.

Feature extraction is another important component of machine learning. It involves transforming raw data into numerical representations that can be understood by machine learning models. Techniques such as TF-IDF (Term Frequency-Inverse Document Frequency), word embeddings, and statistical feature extraction are commonly used for text-based data. In cyber security systems, feature extraction helps in identifying patterns associated with malicious behavior, such as unusual query structures or suspicious keywords.

Machine learning models can be broadly categorized into different algorithms, including decision trees, support vector machines, k-nearest neighbors, and neural networks. Among these,

artificial neural networks (ANNs) are widely used due to their ability to model complex relationships in data. Deep learning, a subset of machine learning, uses multiple layers of neural networks to process large volumes of data and achieve high accuracy. In cyber security, deep learning models such as Convolutional Neural Networks (CNNs) are used to detect patterns in scripts and network traffic.

Model training involves feeding the processed data into the algorithm and adjusting its parameters to minimize errors. This is typically done using optimization techniques such as gradient descent or advanced algorithms like the Levenberg-Marquardt method. After training, the model is evaluated using performance metrics such as accuracy, precision, recall, and F1-score. These metrics help in assessing how well the model performs in detecting threats and minimizing false positives.

One of the key advantages of machine learning is its adaptability. Unlike traditional systems, machine learning models can continuously learn from new data and improve their performance over time. This is particularly important in cyber security, where attack patterns constantly evolve. Machine learning enables systems to detect both known and unknown threats by analyzing behavior rather than relying solely on predefined signatures.

However, machine learning also has some limitations. It requires large amounts of high-quality data for training, and the performance of the model depends heavily on the quality of this data. Additionally, some models can be computationally expensive and require significant processing power. Despite these challenges, the benefits of machine learning outweigh its limitations, making it a powerful tool in modern applications.

In this project, machine learning is used to detect cyber security threats such as SQL Injection, XSS attacks, and malicious URLs. The system processes user inputs, extracts relevant features, and uses trained models to classify inputs as malicious or benign. By integrating machine learning techniques, the system achieves higher accuracy, faster detection, and improved adaptability compared to traditional methods.

Overall, machine learning provides an intelligent and data-driven approach to solving complex problems. Its ability to learn from data, adapt to new situations, and provide accurate predictions makes it an essential component in modern cyber security systems. As technology continues to evolve, machine learning will play an even greater role in enhancing security, improving efficiency, and supporting decision-making processes across various domains.

6.1.3 CATEGORIES OF MACHINE LEARNING

At the most fundamental level, machine learning can be categorized into two main types: supervised learning and unsupervised learning.

Supervised learning involves somehow modeling the relationship between measured features of data and some label associated with the data; once this model is determined, it can be used to apply labels to new, unknown data. This is further subdivided into classification tasks and regression tasks: in classification, the labels are discrete categories, while in regression, the labels are continuous quantities. We will see examples of both types of supervised learning in the following section.

Unsupervised learning involves modeling the features of a dataset without reference to any label, and is often described as letting the dataset speak for itself.

Clustering algorithms identify distinct groups of data, while dimensionality reduction algorithms search for more succinct representations of the data. We will see examples of both types of unsupervised learning in the following section.

6.1.4 NEED FOR MACHINE LEARNING

Human beings, at this moment, are the most intelligent and advanced species on earth because they can think, evaluate and solve complex problems. On the other side, AI is still in its initial stage and haven't surpassed human intelligence in many aspects. Then the question is that what is the need to make machine learn? The most suitable reason for doing this is, "to make decisions, based on data, with efficiency and scale".

The most suitable reason for doing this is, "to make decisions, based on data, with efficiency and scale". Lately, organizations are investing heavily in newer technologies like Artificial Intelligence, Machine Learning and Deep Learning to get the key information from data to perform several real-world tasks and solve problems. We can call it data-driven decisions taken by machines, particularly to automate the process. These data-driven decisions can be used, instead of using programing logic, in the problems that cannot be programmed inherently. The fact is that we can't do without human intelligence, but other aspect is that we all need to solve real-world problems with efficiency at a huge scale. That is why the need for machine learning arises.

6.1.5 CHALLENGES IN MACHINE LEARNING

While Machine Learning is rapidly evolving, making significant strides with cybersecurity and autonomous cars, this segment of AI as whole still has a long way to go. The reason behind is that ML has not been able to overcome number of challenges. The challenges that ML is facing currently are –

Quality of data − Having good-quality data for ML algorithms is one of the biggest challenges. Use of low-quality data leads to the problems related to data preprocessing and feature extraction.

Time-Consuming task − Another challenge faced by ML models is the consumption of time especially for data acquisition, feature extraction and retrieval.

Lack of specialist persons − As ML technology is still in its infancy stage, availability of expert resources is a tough job.

No clear objective for formulating business problems − Having no clear objective and well-defined goal for business problems is another key challenge for ML because this technology is not that mature yet.

Issue of overfitting & underfitting − If the model is overfitting or underfitting, it cannot be represented well for the problem.

Curse of dimensionality − Another challenge ML model faces is too many features of data points. This can be a real hindrance.

Difficulty in deployment − Complexity of the ML model makes it quite difficult to be deployed in real life.

Applications of Machines Learning

Machine Learning is the most rapidly growing technology and according to researchers we are in the golden year of AI and ML. It is used to solve many real-world complex problems which cannot be solved with traditional approach. Following are some real-world applications of ML −

- Emotion analysis
- Sentiment analysis
- Error detection and prevention
- Weather forecasting and prediction
- Stock market analysis and forecasting
- Speech synthesis
- Speech recognition
- Customer segmentation
- Object recognition

How to start learning ML?

This is a rough roadmap you can follow on your way to becoming an insanely talented Machine Learning Engineer. Of course, you can always modify the steps according to your needs to reach your desired end-goal.

Step 1 – Understand the Prerequisites

In case you are a genius, you could start ML directly but normally, there are some prerequisites that you need to know which include Linear Algebra, Multivariate Calculus, Statistics, and Python. And if you don't know these, never fear! You don't need a Ph.D. degree in these topics to get started but you do need a basic understanding.

Learn Linear Algebra and Multivariate Calculus:

Both Linear Algebra and Multivariate Calculus are important in Machine Learning. However, the extent to which you need them depends on your role as a data scientist. If you are more focused on application heavy machine learning, then you will not be that heavily focused on math as there are many common libraries available. But if you want to focus on R&D in Machine Learning, then mastery of Linear Algebra and Multivariate Calculus is very important as you will have to implement many ML algorithms from scratch.

(a) Learn Statistics:

Data plays a huge role in Machine Learning. In fact, around 80% of your time as an ML expert will be spent collecting and cleaning data. And statistics is a field that handles the collection, analysis, and presentation of data. So it is no surprise that you need to learn it!!! Some of the key concepts in statistics that are important are Statistical Significance, Probability Distributions, Hypothesis Testing, Regression, etc. Also, Bayesian Thinking is also a very important part of ML which deals with various concepts like Conditional Probability, Priors, and Posteriors, Maximum Likelihood, etc.

(b) Learn Python:

Some people prefer to skip Linear Algebra, Multivariate Calculus and Statistics and learn them as they go along with trial and error. But the one thing that you absolutely cannot skip is Python. While there are other languages you can use for Machine Learning like R, Scala, etc. Python is currently the most popular language for ML. In fact, there are many Python libraries that are specifically useful for Artificial Intelligence and Machine Learning such as Keras, TensorFlow, Scikit-learn, etc.

Step 2 – Learn Various ML Concepts

Now that you are done with the prerequisites, you can move on to actually learning ML (Which is the fun part!!!) It's best to start with the basics and then move on to the more complicated stuff. Some of the basic concepts in ML are:

(a) Terminologies of Machine Learning

- **Model –** A model is a specific representation learned from data by applying some machine learning algorithm. A model is also called a hypothesis.
- **Feature –** A feature is an individual measurable property of the data. A set of numeric features can be conveniently described by a feature vector. Feature vectors are fed as input to the model. For example, in order to predict a fruit, there may be features like color, smell, taste, etc.
- **Target (Label) –** A target variable or label is the value to be predicted by our model. For the fruit example discussed in the feature section, the label with each set of input would be the name of the fruit like apple, orange, banana, etc.
- **Training –** The idea is to give a set of inputs(features) and it's expected outputs(labels), so after training, we will have a model (hypothesis) that will then map new data to one of the categories trained on.
- **Prediction –** Once our model is ready, it can be fed a set of inputs to which it will provide a predicted output(label).

(b) Types of Machine Learning

- **Supervised Learning –** This involves learning from a training dataset with labeled data using classification and regression models. This learning process continues until the required level of performance is achieved.
- **Unsupervised Learning –** This involves using unlabeled data and then finding the underlying structure in the data in order to learn more and more about the data itself using factor and cluster analysis models.
- **Semi-supervised Learning –** This involves using unlabeled data like Unsupervised Learning with a small amount of labeled data. Using labeled data vastly increases the learning accuracy and is also more cost-effective than Supervised Learning.
- **Reinforcement Learning –** This involves learning optimal actions through trial and error. So, the next action is decided by learning behaviors that are based on the current state and that will maximize the reward in the future.

Machine Learning is broadly categorized into supervised, unsupervised, semi-supervised, and reinforcement learning, each suited for different types of data and problem scenarios. While supervised learning works well with labeled data for accurate predictions, unsupervised learning helps in discovering hidden patterns in unlabeled data.

Advantages of Machine learning:

1. **Easily identifies trends and patterns -**

Machine Learning can review large volumes of data and discover specific trends and patterns that would not be apparent to humans. For instance, for an e-commerce website like Amazon, it serves to understand the browsing behaviors and purchase histories of its users to help cater to the right products, deals, and reminders relevant to them. It uses the results to reveal relevant advertisements to them.

2. **No human intervention needed (automation)**

With ML, you don't need to babysit your project every step of the way. Since it means giving machines the ability to learn, it lets them make predictions and also improve the algorithms on their own. A common example of this is anti-virus software; they learn to filter new threats as they are recognized. ML is also good at recognizing spam.

3. **Continuous Improvement**

As ML algorithms gain experience, they keep improving in accuracy and efficiency. This lets them make better decisions. Say you need to make a weather forecast model. As the amount of data you have keeps growing, your algorithms learn to make more accurate predictions faster.

4. **Handling multi-dimensional and multi-variety data**

Machine Learning algorithms are good at handling data that are multi-dimensional and multi- variety, and they can do this in dynamic or uncertain environments.

5. **Wide Applications**

You could be an e-tailer or a healthcare provider and make ML work for you. Where it does apply, it holds the capability to help deliver a much more personal experience to customers while also targeting the right customers.

Disadvantages of Machine Learning

1. **Data Acquisition:**

Machine Learning requires massive data sets to train on, and these should be inclusive/unbiased, and of good quality. There can also be times where they must wait for new data to be generated.

2. Time and Resources

ML needs enough time to let the algorithms learn and develop enough to fulfill their purpose with a considerable amount of accuracy and relevancy. It also needs massive resources to function. This can mean additional requirements of computer power for you.

3. Data Quality Issues:

The effectiveness of machine learning models depends significantly on the quality of the input data used during training. If the data is noisy, incomplete, inconsistent, or biased, the model may learn incorrect patterns, leading to inaccurate predictions. In real-world scenarios, collecting clean and well-structured data is a challenging task, especially in cyber security where data may contain irregular formats, missing values, or redundant information. Poor data quality not only affects model accuracy but also reduces the reliability and trustworthiness of the system. Therefore, extensive preprocessing and validation are required to ensure that the data used is suitable for machine learning applications.

4. Overfitting Problem:

Overfitting is a common issue in machine learning where the model performs exceptionally well on training data but fails to generalize to new or unseen data. This occurs when the model learns not only the underlying patterns but also the noise and irrelevant details present in the training dataset. As a result, the model becomes too specific and loses its ability to make accurate predictions on real-world data. Overfitting can be controlled using techniques such as cross-validation, regularization, and reducing model complexity. Addressing overfitting is essential to ensure that the system remains robust and performs consistently across different datasets.

5. Interpretability Challenges:

Many machine learning models, especially advanced ones like deep neural networks, are often considered “black box” models because their internal decision-making process is not easily understandable. This lack of interpretability makes it difficult to explain how a particular prediction or classification is made. In critical applications such as cyber security, where decisions may impact system safety and user data, understanding the reasoning behind predictions is important. The inability to interpret model behavior can reduce user trust and make debugging or improving the system more challenging.

6.2 PROJECT METHODOLOGY

6.2.1 DATA COLLECTION AND PREPROCESSING

The project begins with the collection of datasets related to cyber security threats such as SQL Injection, Cross-Site Scripting (XSS), and malicious URLs. The dataset includes both normal and malicious inputs, which helps in building a balanced model. The collected data is then processed to remove noise, duplicate entries, and irrelevant information. Preprocessing steps such as data cleaning, normalization, and formatting are applied to convert the raw data into a structured form. This step ensures that the data is suitable for further analysis and improves the overall performance of the system.

6.2.2 DATA CATEGORIZATION AND FEATURE ENGINEERING

After preprocessing, the data is categorized into two main classes: normal and malicious. The malicious data is further divided into different attack types such as SQL Injection, XSS, and malicious URLs. Feature engineering is then performed to extract meaningful attributes from the dataset. These features include query patterns, script structures, and URL characteristics. Feature selection techniques are used to remove unnecessary data and retain only important features, which improves model efficiency and reduces computational complexity.

6.2.3 MODEL SELECTION AND TRAINING

In this step, suitable machine learning algorithms such as Random Forest, Decision Tree, Support Vector Machine, and Naive Bayes are selected for building the model. The processed dataset is used to train these models, where each algorithm learns patterns associated with normal and malicious activities. The training process helps the system understand how different types of cyber threats behave. Multiple models are used to improve accuracy and compare performance.

6.2.4 MODEL EVALUATION

Once the models are trained, they are evaluated using testing data to measure their performance. Evaluation metrics such as accuracy and prediction results are used to analyze how well the model performs in detecting cyber threats. This step helps in identifying the most suitable model for the system. It also ensures that the system provides reliable and consistent results.

6.2.5 REAL-TIME INPUT PROCESSING AND PREDICTION

The system is designed to handle real-time inputs such as user queries, scripts, and URLs. The input is processed using the same preprocessing and feature extraction techniques applied during training. This ensures consistency in the system. The trained models analyze the input data and predict whether it is normal or malicious. This step enables real-time detection of cyber threats.

6.2.6 RESULT GENERATION AND ALERT SYSTEM

After prediction, the system generates output indicating whether the input is safe or represents a cyberattack. If a malicious activity is detected, the system provides an alert to the user. This helps in taking immediate action to prevent potential threats. The output is displayed in a simple and understandable format, making it easy for users to interpret the results.

6.2.7 SYSTEM INTEGRATION AND DEPLOYMENT

All modules such as data collection, preprocessing, feature extraction, model training, and prediction are integrated into a single system. The application is developed using Python and Flask, which helps in connecting the user interface with the backend processing. The system is designed to be scalable and can be deployed in different environments. It supports real-time operation and can be updated with new data to improve performance over time.

Libraries installed in Project

pip install numpy

pip install pandas

pip install scikit-learn

pip install matplotlib

pip install seaborn

pip install flask

pip install mysql-connector-python

The project uses several Python libraries to support data processing, machine learning, and system development. These libraries provide built-in functions that simplify implementation and improve system performance. They help in handling datasets, performing computations, and building models efficiently.

NumPy:

Used for numerical computations and handling multi-dimensional arrays. It provides functions for mathematical operations required during data processing.

Pandas:

Used for data manipulation and analysis. It helps in reading datasets, cleaning data, and organizing it into structured formats such as data frames.

Scikit-learn:

Used for implementing machine learning algorithms such as Random Forest, Decision Tree, Support Vector Machine, and Naive Bayes. It also provides tools for model training and evaluation.

Matplotlib:

Used for data visualization. It helps in plotting graphs and charts to analyze model performance and data patterns.

Seaborn:

Used for advanced data visualization. It provides better visualization of data distributions and relationships between variables.

Flask:

Used for building the application and connecting the front-end with backend processing. It handles user requests and displays results.

MySQL Connector:

Used for connecting Python with the MySQL database. It helps in storing and retrieving data efficiently.

6.3 CODING

```
from flask import Flask, request, jsonify, render_template
import numpy as np
import joblib
import pickle
from tensorflow.keras.models import load_model
from scipy.sparse import hstack
import cv2
import re
from flask import Flask, render_template, request, jsonify
import requests
from bs4 import BeautifulSoup

app = Flask(__name__)

# Load models
xss_model = load_model('models/xss_model.h5')
url_model = joblib.load('models/BestModel_ExtraTreesClassifier.joblib')
sql_injection_model = joblib.load('models/saved_model.pkl')

# Load additional resources
with open('models/train_bow', 'rb') as f:
    train_bow = pickle.load(f)
import re
import string
import logging
import numpy as np
import pandas as pd

import seaborn as sns
import matplotlib.pyplot as plt
from urllib.parse import urlparse
from sklearn.model_selection import train_test_split, cross_val_score, cross_val_predict
from sklearn.metrics import accuracy_score, recall_score, precision_score, f1_score,
```

```
classification_report, confusion_matrix
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, ExtraTreesClassifier,
GradientBoostingClassifier, BaggingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import SGDClassifier, LogisticRegression, RidgeClassifier, Perceptron
from sklearn.naive_bayes import GaussianNB, MultinomialNB
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier
from sklearn.gaussian_process import GaussianProcessClassifier
from sklearn.mixture import GaussianMixture
from sklearn.cluster import KMeans
from sklearn.pipeline import Pipeline
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis,
QuadraticDiscriminantAnalysis
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier
from catboost import CatBoostClassifier

from tldextract import extract as tld_extract
from tld import get_tld, is_tld
from tld.exceptions import TldDomainNotFound, TldBadUrl, TldIOError

from colorama import Fore
from datetime import datetime
from plotly.subplots import make_subplots
from plotly import graph_objects as go
from wordcloud import WordCloud

from gensim.models import Word2Vec
import tldextract
import hashlib
import whois
import warnings
```

```
warnings.filterwarnings("ignore")
def get_numerical_values(url):
    url = url.replace('www.', '')
    url_len = get_url_length(url)
    letters_count = count_letters(url)
    digits_count  = count_digits(url)
    special_chars_count = count_special_chars(url)
    shortened = has_shortening_service(url)
    abnormal = abnormal_url(url)
    secure_https = secure_http(url)
    have_ip = have_ip_address(url)

    parsed_url  = urlparse(url)
    root_domain = parsed_url.netloc.split(".")[-2]
    url_region = get_url_region(root_domain)

    return {
        'url_len': url_len,
        'letters_count': letters_count,
        'digits_count': digits_count,
        'special_chars_count': special_chars_count,
        'shortened': shortened,
        'abnormal': abnormal,
        'secure_http': secure_https,
        'have_ip': have_ip,
        'url_region': hash_encode(url_region),

        'root_domain': hash_encode(root_domain)
    }

def get_url_length(url):
    return len(url)
def extract_pri_domain(url):
```

```
    try:
        res = get_tld(url, as_object = True, fail_silently=False,fix_protocol=True)
        pri_domain= res.parsed_url.netloc
    except :
        pri_domain= None
    return pri_domain
def count_letters(url):
    num_letters = sum(char.isalpha() for char in url)
    return num_letters

def count_digits(url):
    num_digits = sum(char.isdigit() for char in url)
    return num_digits
def count_special_chars(url):
    special_chars = "!@#$%^&*()_+-=[]{};:,.<>/?~|"

    num_special_chars = sum(char in special_chars for char in url)
    return num_special_chars
def has_shortening_service(url):
    pattern = re.compile(r'bit\.ly|goo\.gl|shorte\.st|go2l\.ink|x\.co|ow\.ly|t\.co|tinyurl|tr\.im|is\.gd|cli\.gs|'
                         r'yfrog\.com|migre\.me|ff\.im|tiny\.cc|url4\.eu|twit\.ac|su\.pr|twurl\.nl|snipurl\.com|'
                         r'short\.to|BudURL\.com|ping\.fm|post\.ly|Just\.as|bkite\.com|snipr\.com|fic\.kr|loopt\.u
s|'
                        r'doiop\.com|short\.ie|kl\.am|wp\.me|rubyurl\.com|om\.ly|to\.ly|bit\.do|t\.co|lnkd\.in|'
                         r'db\.tt|qr\.ae|adf\.ly|goo\.gl|bitly\.com|cur\.lv|tinyurl\.com|ow\.ly|bit\.ly|ity\.im|'
                         r'q\.gs|is\.gd|po\.st|bc\.vc|twitthis\.com|u\.to|j\.mp|buzurl\.com|cutt\.us|u\.bb|yourls\.org|'
                         r'x\.co|prettylinkpro\.com|scrnch\.me|filoops\.info|vzturl\.com|qr\.net|1url\.com|tweez\.
me|v\.gd|'
                         r'tr\.im|link\.zip\.net')
    match = pattern.search(url)
    return int(bool(match))
def abnormal_url(url):
    parsed_url = urlparse(url)
    hostname = parsed_url.hostname
```

```
    if hostname:
        hostname = str(hostname)
        match = re.search(hostname, url)
        if match:
            return 1
    return 0
def secure_http(url):
    scheme = urlparse(url).scheme
    if scheme == 'https':
        return 1
    else:
        return 0
def have_ip_address(url):
    pattern = r'(([01]?\d\d?|2[0-4]\d|25[0-5])\.([01]?\d\d?|2[0-4]\d|25[0-5])\.([01]?\d\d?|2[0-4]\d|25[0-
5])\.' \
            r'([01]?\d\d?|2[0-4]\d|25[0-5])\/)|' \
            r'(([01]?\d\d?|2[0-4]\d|25[0-5])\.([01]?\d\d?|2[0-4]\d|25[0-5])\.([01]?\d\d?|2[0-4]\d|25[0-5])\.' \
            r'([01]?\d\d?|2[0-4]\d|25[0-5])\/)|' \

            r'((0x[0-9a-fA-F]{1,2})\.(0x[0-9a-fA-F]{1,2})\.(0x[0-9a-fA-F]{1,2})\.(0x[0-9a-fA-
F]{1,2})\/)' \
            r'(?:[a-fA-F0-9]{1,4}:){7}[a-fA-F0-9]{1,4}|' \
            r'([0-9]+(?:\.[0-9]+){3}:[0-9]+)|' \
            r'((?:(?:\d|[01]?\d\d|2[0-4]\d|25[0-5])\.){3}(?:25[0-5]|2[0-4]\d|[01]?\d\d|\d)(?:\/\d{1,2})?)'

    match = re.search(pattern, url)
    if match:
        return 1
    else:
        return 0
def get_url_region(primary_domain):
    ccTLD_to_region = {
    ".ac": "Ascension Island",
    ".ad": "Andorra",
```

".ae": "United Arab Emirates",
".af": "Afghanistan",
".ag": "Antigua and Barbuda",
".ai": "Anguilla",
".al": "Albania",
".am": "Armenia",
".an": "Netherlands Antilles",
".ao": "Angola",
".aq": "Antarctica",
".ar": "Argentina",
".as": "American Samoa",
".at": "Austria",
".au": "Australia",
".aw": "Aruba",
".ax": "Åland Islands",
".az": "Azerbaijan",
".ba": "Bosnia and Herzegovina",
".bb": "Barbados",
".bd": "Bangladesh",
".be": "Belgium",
".bf": "Burkina Faso",
".bg": "Bulgaria",
".bh": "Bahrain",
".bi": "Burundi",
".bj": "Benin",
".bm": "Bermuda",
".bn": "Brunei Darussalam",
".bo": "Bolivia",
".br": "Brazil",
".bs": "Bahamas",
".bt": "Bhutan",
".bv": "Bouvet Island",
".bw": "Botswana",
".by": "Belarus",

".bz": "Belize",

".ca": "Canada",

".cc": "Cocos Islands",

".cd": "Democratic Republic of the Congo",

".cf": "Central African Republic",

".cg": "Republic of the Congo",

".ch": "Switzerland",

".ci": "Côte d'Ivoire",

".ck": "Cook Islands",

".cl": "Chile",

".cm": "Cameroon",

".cn": "China",

".co": "Colombia",

".cr": "Costa Rica",

".cu": "Cuba",

".cv": "Cape Verde",

".cw": "Curaçao",

".cx": "Christmas Island",

".cy": "Cyprus",

".cz": "Czech Republic",

".de": "Germany",

".dj": "Djibouti",

".dk": "Denmark",

".dm": "Dominica",

".do": "Dominican Republic",

".dz": "Algeria",

".ec": "Ecuador",

".ee": "Estonia",

".eg": "Egypt",

".er": "Eritrea",

".es": "Spain",

".et": "Ethiopia",

".eu": "European Union",

".fi": "Finland",

".fj": "Fiji",
".fk": "Falkland Islands",
".fm": "Federated States of Micronesia",
".fo": "Faroe Islands",
".fr": "France",
".ga": "Gabon",
".gb": "United Kingdom",
".gd": "Grenada",
".ge": "Georgia",
".gf": "French Guiana",
".gg": "Guernsey",
".gh": "Ghana",
".gi": "Gibraltar",
".gl": "Greenland",
".gm": "Gambia",
".gn": "Guinea",
".gp": "Guadeloupe",
".gq": "Equatorial Guinea",
".gr": "Greece",
".gs": "South Georgia and the South Sandwich Islands",
".gt": "Guatemala",
".gu": "Guam",
".gw": "Guinea-Bissau",
".gy": "Guyana",
".hk": "Hong Kong",
".hm": "Heard Island and McDonald Islands",
".hn": "Honduras",
".hr": "Croatia",
".ht": "Haiti",
".hu": "Hungary",
".id": "Indonesia",
".ie": "Ireland",
".il": "Israel",
".im": "Isle of Man",

".in": "India",

".io": "British Indian Ocean Territory",

".iq": "Iraq",

".ir": "Iran",

".is": "Iceland",

".it": "Italy",

".je": "Jersey",

".jm": "Jamaica",

".jo": "Jordan",

".jp": "Japan",

".ke": "Kenya",

".kg": "Kyrgyzstan",

".kh": "Cambodia",

".ki": "Kiribati",

".km": "Comoros",

".kn": "Saint Kitts and Nevis",

".kp": "Democratic People's Republic of Korea (North Korea)",

".kr": "Republic of Korea (South Korea)",

".kw": "Kuwait",

".ky": "Cayman Islands",

".kz": "Kazakhstan",

".la": "Laos",

".lb": "Lebanon",

".lc": "Saint Lucia",

".li": "Liechtenstein",

".lk": "Sri Lanka",

".lr": "Liberia",

".ls": "Lesotho",

".lt": "Lithuania",

".lu": "Luxembourg",

".lv": "Latvia",

".ly": "Libya",

".ma": "Morocco",

".mc": "Monaco",

".md": "Moldova",
".me": "Montenegro",
".mf": "Saint Martin (French part)",
".mg": "Madagascar",
".mh": "Marshall Islands",
".mk": "North Macedonia",
".ml": "Mali",
".mm": "Myanmar",
".mn": "Mongolia",
".mo": "Macao",
".mp": "Northern Mariana Islands",
".mq": "Martinique",
".mr": "Mauritania",
".ms": "Montserrat",
".mt": "Malta",
".mu": "Mauritius",
".mv": "Maldives",
".mw": "Malawi",
".mx": "Mexico",
".my": "Malaysia",
".mz": "Mozambique",
".na": "Namibia",
".nc": "New Caledonia",
".ne": "Niger",
".nf": "Norfolk Island",
".ng": "Nigeria",
".ni": "Nicaragua",
".nl": "Netherlands",
".no": "Norway",
".np": "Nepal",
".nr": "Nauru",
".nu": "Niue",
".nz": "New Zealand",
".om": "Oman",

".pa": "Panama",
".pe": "Peru",
".pf": "French Polynesia",
".pg": "Papua New Guinea",
".ph": "Philippines",
".pk": "Pakistan",
".pl": "Poland",
".pm": "Saint Pierre and Miquelon",
".pn": "Pitcairn",
".pr": "Puerto Rico",
".ps": "Palestinian Territory",
".pt": "Portugal",
".pw": "Palau",
".py": "Paraguay",
".qa": "Qatar",
".re": "Réunion",
".ro": "Romania",
".rs": "Serbia",
".ru": "Russia",
".rw": "Rwanda",
".sa": "Saudi Arabia",
".sb": "Solomon Islands",
".sc": "Seychelles",
".sd": "Sudan",
".se": "Sweden",
".sg": "Singapore",
".sh": "Saint Helena",
".si": "Slovenia",
".sj": "Svalbard and Jan Mayen",
".sk": "Slovakia",
".sl": "Sierra Leone",
".sm": "San Marino",
".sn": "Senegal",
".so": "Somalia",

".sr": "Suriname",

".ss": "South Sudan",

".st": "São Tomé and Príncipe",

".sv": "El Salvador",

".sx": "Sint Maarten (Dutch part)",

".sy": "Syria",

".sz": "Eswatini",

".tc": "Turks and Caicos Islands",

".td": "Chad",

".tf": "French Southern Territories",

".tg": "Togo",

".th": "Thailand",

".tj": "Tajikistan",

".tk": "Tokelau",

".tl": "Timor-Leste",

".tm": "Turkmenistan",

".tn": "Tunisia",

".to": "Tonga",

".tr": "Turkey",

".tt": "Trinidad and Tobago",

".tv": "Tuvalu",

".tw": "Taiwan",

".tz": "Tanzania",

".ua": "Ukraine",

".ug": "Uganda",

".uk": "United Kingdom",

".us": "United States",

".uy": "Uruguay",

".uz": "Uzbekistan",

".va": "Vatican City",

".vc": "Saint Vincent and the Grenadines",

".ve": "Venezuela",

".vg": "British Virgin Islands",

".vi": "U.S. Virgin Islands",

```
    ".vn": "Vietnam",
    ".vu": "Vanuatu",
    ".wf": "Wallis and Futuna",
    ".ws": "Samoa",
    ".ye": "Yemen",
    ".yt": "Mayotte",
    ".za": "South Africa",
    ".zm": "Zambia",
    ".zw": "Zimbabwe"
    }

    for ccTLD in ccTLD_to_region:
        if primary_domain.endswith(ccTLD):
            return ccTLD_to_region[ccTLD]

    return "Global"
def extract_root_domain(url):
    extracted = tldextract.extract(url)
    root_domain = extracted.domain
    return root_domain
def hash_encode(category):
    hash_object = hashlib.md5(category.encode())
    return int(hash_object.hexdigest(), 16) % (10 ** 8)

# In[99]:

def model_predict(url):
    class_mapping = {
        0: 'benign',
        1: 'defacement',
        2: 'phishing',
        3: 'malware'
    }
    numerical_values = get_numerical_values(url)
```

```
    prediction_int = pipeline.predict(np.array(list(numerical_values.values())).reshape(1, -1))[0]
    prediction_label = class_mapping.get(prediction_int, 'Unknown')
    return prediction_int, prediction_label

# Preprocessing functions
def preprocess_xss(sentence):
    sentence_ascii = [ord(char) for char in sentence if ord(char) <= 128]
    zer = np.zeros((10000))
    for i, val in enumerate(sentence_ascii[:10000]):
        zer[i] = val
    image = cv2.resize(zer.reshape((100, 100)), (100, 100), interpolation=cv2.INTER_CUBIC)
    return image.reshape(1, 100, 100, 1) / 128  # Normalize

def preprocess_url(url):
    # Placeholder for actual preprocessing
    # Replace `get_numerical_values` with the actual implementation
    numerical_values = get_numerical_values(url)
    return np.array(list(numerical_values.values())).reshape(1, -1)

def preprocess_sql(query):
    def process(x, pattern):
        return len(re.findall(pattern, x))

    def combined_keywords(x):
        patterns = [r'null', r'chr', r'char']
        return sum(len(re.findall(p, x)) for p in patterns)

    def genuine(x):
        genuine_keys = ['select', 'top', 'order', 'fetch', 'join', 'avg', 'count', 'sum', 'rows']
        return sum(x.split().count(key) for key in genuine_keys)

    preprocessed_query = [
        process(query, """),
```

```
        process(query, ""),
        process(query, r"[!\"#$%&'()*+,-./:;<=>?@[\\]^_`{|}~]"),
        process(query, r'(--)'),
        process(query, r'(\/\*)'),
        process(query, r'\s+'),
        process(query, r"%"),
        process(query, r'\snot\s|\sand\s|\sor\s|\sxor\s|&&|\|\||!'),
        process(query, r'"\+|-|[^\/]\*|\/[^\*]"'),
        process(query, "null"),
        process(query, r'0[xX][0-9a-fA-F]+\s'),
        process(query, r'[a-zA-Z]'),
        process(query, r'[0-9]'),
        combined_keywords(query),
        genuine(query)
    ]
    unigram_bow = train_bow.transform([query])
    return hstack((unigram_bow, preprocessed_query))

# Route definitions
# Import necessary libraries
from flask import Flask, render_template, request, jsonify



# Route definitions
@app.route('/')
def home():
    return render_template('home.html')

@app.route('/xss', methods=['GET', 'POST'])

def xss():
    if request.method == "POST":
        # Ensure the incoming request is JSON
        if not request.is_json:
```

```
            return jsonify({"error": "Content-Type must be application/json"}), 415

        # Parse JSON safely
        input_data = request.get_json(silent=True) or {}
        input_text = input_data.get('input_text', '').strip().lower()

        if not input_text:
            return jsonify({"error": "Invalid input"}), 400

        # Preprocess and predict
        processed = preprocess_xss(input_text)
        prediction = xss_model.predict(processed)[0][0]
        result = "Attack Detected" if prediction > 0.5 else "Benign"

        return jsonify({
            "input": input_text,
            "type": "xss",
            "result": result
        })

    return render_template('xss.html')

@app.route('/sql', methods=['GET', 'POST'])
def sql():
    if request.method == 'POST':

        print("xss input recived")
        input_data = request.get_json()
        input_text = input_data.get('input_text', '').lower()

        if not input_text:
            return jsonify({"error": "Invalid input"}), 400

        # Placeholder: Preprocess and predict for SQL Injection
```

```
        processed = preprocess_sql(input_text)
        prediction = sql_injection_model.predict(processed)[0]
        result = "SQL Injection Detected" if prediction == 1 else "Benign Query"

        return jsonify({
            "input": input_text,
            "type": "sql",
            "result": result
        })

    return render_template('sql.html')

@app.route('/url', methods=['GET', 'POST'])
def url():
    if request.method == 'POST':
        print("xss input recived")
        input_data = request.get_json()
        input_text = input_data.get('input_text', '').lower()

        if not input_text:
            return jsonify({"error": "Invalid input"}), 400

        # Placeholder: Preprocess and predict for Malicious URL
        processed = preprocess_url(input_text)
        prediction = url_model.predict(processed)[0]
        result = "Malicious" if prediction else "Safe"

        return jsonify({
            "input": input_text,
            "type": "url",
            "result": result
        })

    return render_template('url.html')
```

```
def check_sql_injection(url):
    test_payload = "' OR '1'='1"
    try:
        response = requests.get(f"{url}?id={test_payload}", timeout=5)
        if "syntax error" in response.text.lower() or "database" in response.text.lower():
            return True
    except requests.exceptions.RequestException:
        pass
    return False

# Helper Function to Check for Missing Security Headers
def check_security_headers(response):
    vulnerabilities = []
    headers = response.headers

    if "Content-Security-Policy" not in headers:
        vulnerabilities.append("Missing Content-Security-Policy header.")

    if "X-Content-Type-Options" not in headers:
        vulnerabilities.append("Missing X-Content-Type-Options header.")
    if "Strict-Transport-Security" not in headers:
        vulnerabilities.append("Missing Strict-Transport-Security header.")
    if "X-Frame-Options" not in headers:
        vulnerabilities.append("Missing X-Frame-Options header.")

    return vulnerabilities

# Helper Function to Check for XSS Vulnerabilities
def check_xss(url):
    vulnerabilities = []
    try:
        response = requests.get(url, timeout=5)
        soup = BeautifulSoup(response.text, 'html.parser')
        forms = soup.find_all("form")
```

```
        for form in forms:
            action = form.get("action") or ""
            inputs = form.find_all("input")
            for input_tag in inputs:
                name = input_tag.get("name")
                if name:
                    xss_payload = "<script>alert('XSS')</script>"
                    target_url = url + action
                    xss_test = requests.post(target_url, data={name: xss_payload}, timeout=5)
                    if xss_payload in xss_test.text:
                        vulnerabilities.append(f"Potential XSS vulnerability in form: {action}")
    except requests.exceptions.RequestException:
        pass

    return vulnerabilities

# Home Page with Input Form
@app.route('/index2')
def index2():
    return render_template('index2.html')

# Scan URL and Display Results
@app.route('/scan', methods=['POST'])
def scan_website():
    input_url = request.form.get("url")

    # Validate URL input
    if not input_url:
        return render_template("index.html", error="Please provide a URL to scan.")

    # Add protocol if missing
    if not input_url.startswith(('http://', 'https://')):
        input_url = f"http://{input_url}"
```

```
    # Initialize results dictionary
    results = {"url": input_url, "vulnerabilities": [], "headers": {}, "xss_forms": []}

    try:
        headers = {'User-Agent': 'Mozilla/5.0'}
        response = requests.get(input_url, headers=headers, timeout=10)
        results["headers"] = dict(response.headers)  # Store headers for display

        if check_sql_injection(input_url):
            results["vulnerabilities"].append("Potential SQL Injection detected.")

        # Check Missing Headers
        header_vulnerabilities = check_security_headers(response)
        results["vulnerabilities"].extend(header_vulnerabilities)

        # Check XSS Vulnerabilities
        xss_vulnerabilities = check_xss(input_url)
        results["xss_forms"].extend(xss_vulnerabilities)

    except requests.exceptions.Timeout:
        return render_template("index2.html", error="Connection timed out. Please try again.")
    except requests.exceptions.ConnectionError:
        return render_template("index2.html", error="Failed to connect to the URL. Please check the
address.")
    except Exception as e:
        return render_template("index2.html", error=f"An unexpected error occurred: {str(e)}")

    return render_template("results.html", results=results)

if __name__ == '__main__':
    app.run(debug=True)
```

7. SYSTEM TESTING

System testing is a critical activity that ensures the developed cyberbullying detection system performs accurately, consistently, and reliably under real operating conditions. The primary purpose of testing is to identify potential defects, validate system behavior, and confirm that all functional and nonfunctional requirements have been met.

In this project, system testing focuses on validating every major module, including front-end interfaces, Django backend services, preprocessing components, and the ensemble-based classification engine integrating Boosted Decision Tree (BoostDT) and Bagging Random Forest (BagRF) through Soft Voting. Testing verifies that user interactions, dataset handling, model prediction logic, and output presentation operate as expected without failures or inconsistencies.

System testing was performed across multiple scenarios and datasets to ensure correctness, robustness, and usability. Special emphasis was placed on classification behavior, handling of edge-case text inputs, and stability during repeated prediction requests.

7.1 Types of System Testing

7.1.1 Unit Testing

Unit testing was carried out to validate individual software components independently. Each Django view, function, preprocessing routine, and classifier interaction module was executed with controlled input values to verify expected outputs.

Key focus areas included:

- tokenization, normalization, and lemmatization behavior
- TF-IDF feature vector generation
- internal logic of ensemble combination
- database operations for login, registration, and predictions

Unit testing ensured that every internal logical path executed correctly and no unexpected conditions occurred. Failures during this stage would have been easier to isolate and correct before integration.

Unit testing is performed in project during the development phase to verify the correctness of individual components such as preprocessing, feature extraction, and prediction modules. Each module is tested independently to ensure it functions as expected before integrating with the overall system.

7.1.2 Integration Testing

Integration testing examined whether combined components interacted correctly once they were linked together.

Modules tested in combination included:

- front-end request submission with backend API responses
- preprocessing and feature extraction chained with classification
- ensemble model logic when receiving outputs from BoostDT and BagRF
- prediction logging and storage in the database

This testing stage confirmed that individually correct components functioned properly when executed together as a single workflow. Particular attention was paid to ensuring correct feature alignment between models and stability in Soft Voting combination

7.1.3 Functional Testing

Functional testing validated that each feature performed according to specification and user expectations. Test cases simulated actual user scenarios such as registration, login, text submission, and voice-based prediction.

Major validation rules included:

- valid inputs are processed successfully
- invalid or empty inputs are rejected gracefully
- correct cyberbullying category is displayed for each prediction
- navigation links and page workflows operate correctly

Functional testing confirmed that system features were clearly available, usable, and responsive.

7.1.4 System Testing

System testing evaluated the project as a complete application. The focus was on overall reliability, consistency of behavior, and the accuracy of outcomes when used in real conditions.

Tests verified:

- coordinated execution across modules
- correct response to large datasets

- classification accuracy under varying abuse patterns
- stability during repeated sequential predictions

The testing demonstrated that the configuration yields predictable and correct results consistent with documented requirements.

7.1.5 White-Box Testing

White-box testing was applied to internal processing componentsincluding preprocessing pipelines and ensemble computation logic. Testers observed internal variable flows, code execution branches, and probability aggregation to ensure correct model contributions in Soft Voting.

7.1.6 Black-Box Testing

Black-box testing evaluated the system purely from the user's perspective, without examining internal code. Inputs were submitted through user forms and prediction outputs were observed, ensuring that visible system behavior aligned with expected outcomes. This was particularly important in evaluating system usability and error-handling behavior.

7.1.7 Acceptance Testing

Acceptance testing ensured that the system satisfied all documented requirements and enduser expectations. Stakeholders reviewed usability, accuracy, output clarity, and workflow navigation. Feedback confirmed that the system was intuitive, responsive, and aligned with real cyberbullying detection needs.

Test Result Summary:

All defined test cases passed successfully. No major defects were encountered.

Testing Performed

Unit Testing

Unit testing was carried out during the development phase of the Cyber Security Threat Detection System to ensure that each individual module functions correctly before integrating them into the complete system. This type of testing focuses on verifying the smallest functional units of the application, such as individual functions, methods, or components. By testing each unit independently, errors can be identified and corrected at an early stage, which improves overall system reliability and reduces debugging effort later.

In this project, unit testing was mainly applied to core modules such as input handling, data preprocessing, feature extraction, and prediction logic. Since the system processes different types of inputs such as SQL queries, scripts, and URLs, it was important to ensure that each module handles data accurately and consistently.

Modules Tested in Unit Testing

1. Input Handling Module

This module was tested to ensure that it correctly accepts different types of user inputs, including SQL queries, scripts, and URLs. It was verified that the system can handle valid inputs as well as edge cases such as empty input, null values, or incorrect formats. Proper validation checks were implemented to prevent system errors during execution.

2. Data Preprocessing Module

The preprocessing module was tested to verify that it performs operations such as cleaning unwanted characters, normalizing text, and handling special symbols correctly. This module plays a critical role in preparing input data for machine learning models. Testing ensured that the processed output is consistent and suitable for further analysis.

3. Feature Extraction Module

This module was tested to confirm that relevant features are extracted from the input data. It converts textual data into numerical form using techniques such as vectorization. Unit testing ensured that important patterns are captured correctly and unnecessary data is ignored.

4. Machine Learning Model Module

The prediction logic was tested to verify that the trained models correctly classify inputs as malicious or benign. Different sample inputs were used to ensure that the model responds accurately. The module was also tested to ensure that it handles unseen or unusual inputs without crashing.

5. Output Generation Module

This module was tested to ensure that the system displays results correctly to the user. It verifies whether the output is clear, accurate, and properly formatted. Messages such as “Attack Detected” or “Benign Input” were validated for correctness.

7.2 Testing Strategies

A structured testing strategy was followed throughout the project lifecycle. Testing progressed systematically from component-level validation to full-system verification.

7.2.1 Test Strategy and Approach

Testing was performed both manually and programmatically. Detailed execution logs and dataset-based test scripts were used to validate consistency of classifier behavior.

Primary strategic objectives included:

- verifying correctness of text preprocessing and model inputs ensuring ensemble behavior consistently outperformed single classifiers
- verifying error-free interactions between user interface and backend services
- validating prediction reliability under noisy, sarcastic, and ambiguous text

Field testing simulated real-world user activity, while controlled test cases verified logical correctness.

7.2.2 Test Objectives

The following objectives guided all testing activities:

- all fields and forms must operate correctly
- screens and interactions should respond without delay
- invalid or malformed inputs must be handled safely
- predictions should follow expected patterns in comparable research literature
- transitions between system pages must be correct and intuitive

7.2.3 Features Tested

The major system features examined included:

- data entry validation and prevention of duplicate accounts
- correct routing of each navigation link
- prediction accuracy across cyberbullying categories
- correct Soft Voting operation between BoostDT and BagRF

- adherence to expected model training and evaluation workflows

7.2.4 Integration Testing Strategy

Integration testing emphasized early detection of dependency conflicts and data mismatches.

Testing confirmed correct:

- alignment of TF-IDF features with both classifiers
- synchronization of probability outputs into Soft Voting
- interface communication flow with Django APIs

This strategy prevented error propagation into later development stages. Integration testing is a level of software testing in which individual modules or components of a system are combined and tested as a group. The main objective is to verify that different modules interact correctly with each other and work together as expected. Even if individual units function properly, errors can occur when they are integrated, such as interface mismatches, data flow issues, or communication failures.

7.2.5 Acceptance Criteria

A prediction system instance was accepted only when it satisfied these conditions:

- accurate execution of classification pipeline
- stable runtime performance
- error-free navigation and submission
- meaningful categories shown without misinterpretation
- compliance with defined requirements

7.2.6 Overall Test Results

All planned test cases executed successfully. The system demonstrated stable performance, logical correctness, and consistent cyberbullying prediction accuracy. The Soft Voting ensemble consistently produced more reliable outcomes compared to evaluating either single classifier independently.

Test strategies refer to a systematic approach used in software testing to ensure that a product is tested effectively and meets quality standards. They define how testing activities will be carried out, including the methods, tools, techniques, and resources required. A good test strategy helps in identifying defects early, improving software reliability, and reducing development costs.

There are different types of test strategies such as unit testing, which focuses on individual components; integration testing, which checks the interaction between modules; system testing, which validates the complete system; and acceptance testing, which ensures the software meets user requirements. Additionally, strategies like black-box testing and white-box testing are used based on whether the internal code structure is considered or not.

An effective test strategy also includes planning for test data, defining test environments, and setting clear objectives and timelines. It ensures proper documentation, risk management, and continuous improvement in the testing process.

7.3 Sample Test Cases

Test cases:

S No.	TEST CASES	EXPECTED RESULT	RESULT	REMARKS (IF FAIL)
1.	SQL Injection Detection	System should identify malicious SQL query correctly	Pass	-
2.	XSS Attack Detection	System should detect harmful scripts in input	Pass	-
3.	Malicious URL Detection	System should classify harmful URL correctly	Fail	Some complex URLs with encoding were misclassified
4.	Normal Input Detection	System should classify safe input as normal	Pass	-
5.	Data Preprocessing	Data should be cleaned and formatted correctly	Pass	-
6.	Feature Extraction	Relevant features should be extracted from input	Pass	-
7.	Model Prediction Accuracy	Model should give accurate prediction results	Fail	Accuracy drops for unseen or rare attack patterns
8.	Real-Time Input Handling	System should process input without delay	Pass	-
9.	Invalid Input Handling	System should handle incorrect or empty input	Pass	-
10.	System Performance	System should work efficiently without lag	Fail	Slight delay observed with large datasets

Table 7.3 Test Cases

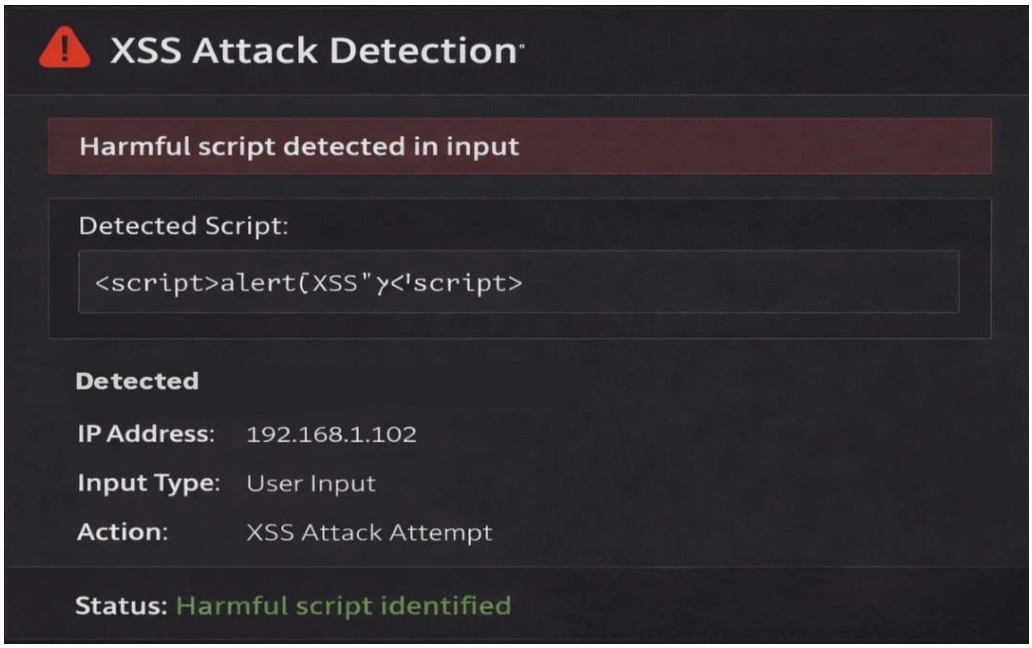


Fig 7.3.1: XSS Attack Detection

Description:

This figure illustrates the detection of a harmful script input. The system analyzes the given script and identifies it as a Cross-Site Scripting (XSS) attack, demonstrating its ability to detect malicious client-side scripts.

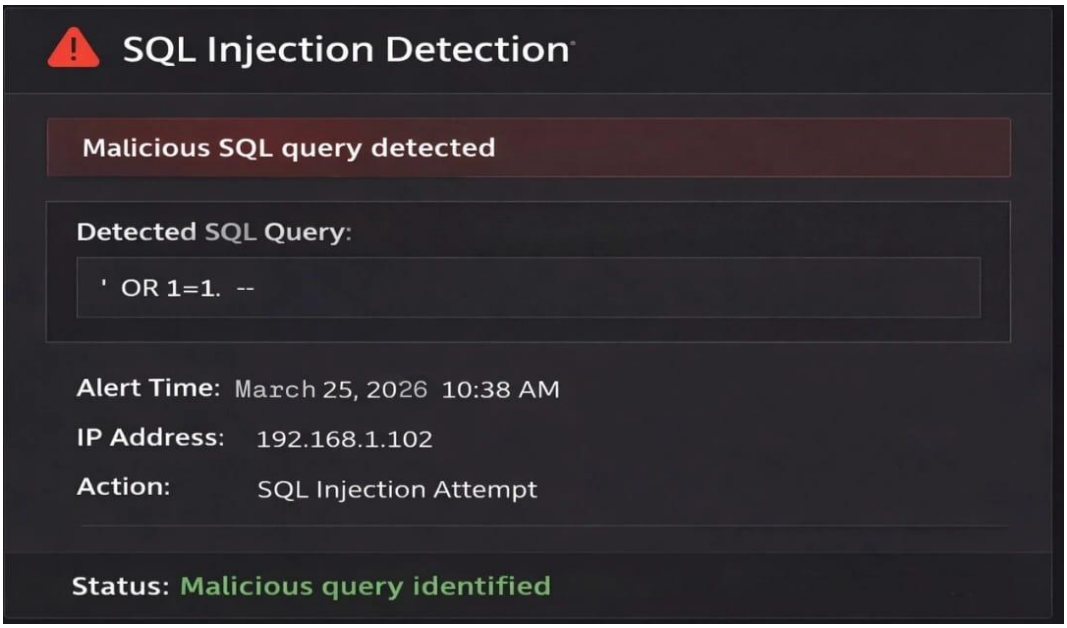


Fig 7.3.2: SQL Injection Detection

Description:

This figure shows the detection of a malicious SQL query entered by the user. The system correctly identifies the injected query and classifies it as an attack, indicating successful detection of SQL Injection vulnerabilities.

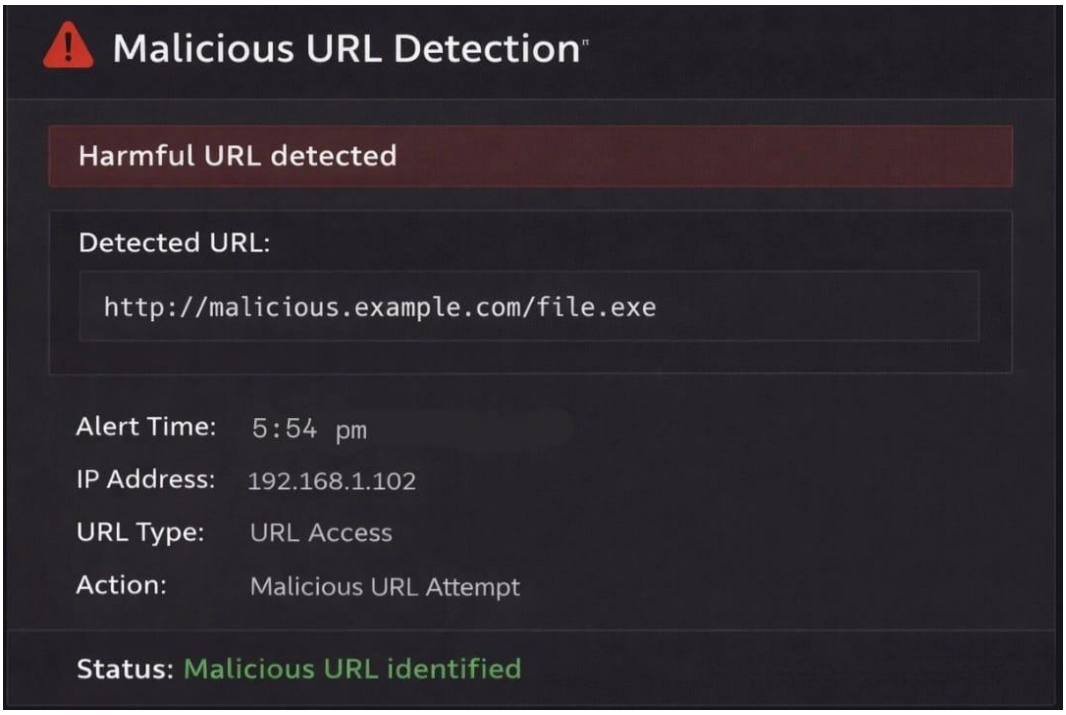


Fig 7.3.3: Malicious URL Detection

Description:

This figure presents the classification of a harmful URL. The system evaluates the input URL and correctly identifies it as malicious, ensuring protection against unsafe web links.

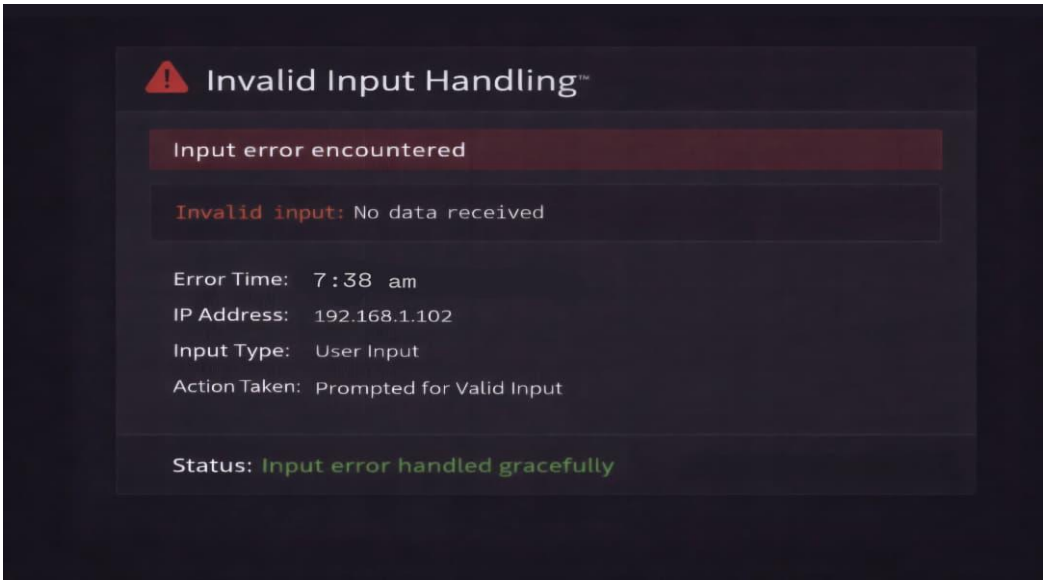


Fig 7.3.4: Invalid Input Handling

Description:

This figure demonstrates how the system handles incorrect or empty input. The system detects invalid input and responds appropriately, ensuring robustness and proper validation mechanisms.

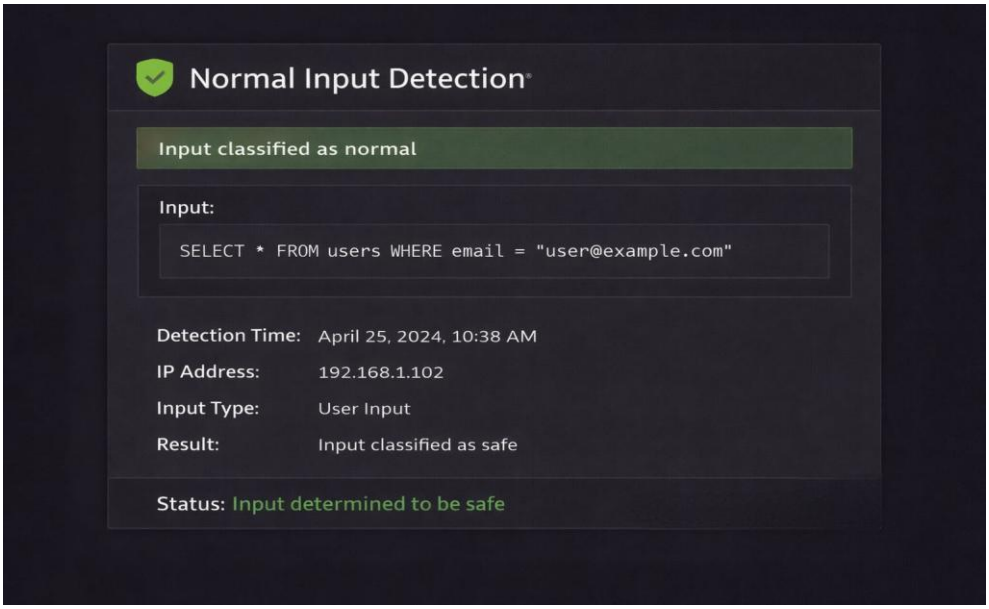
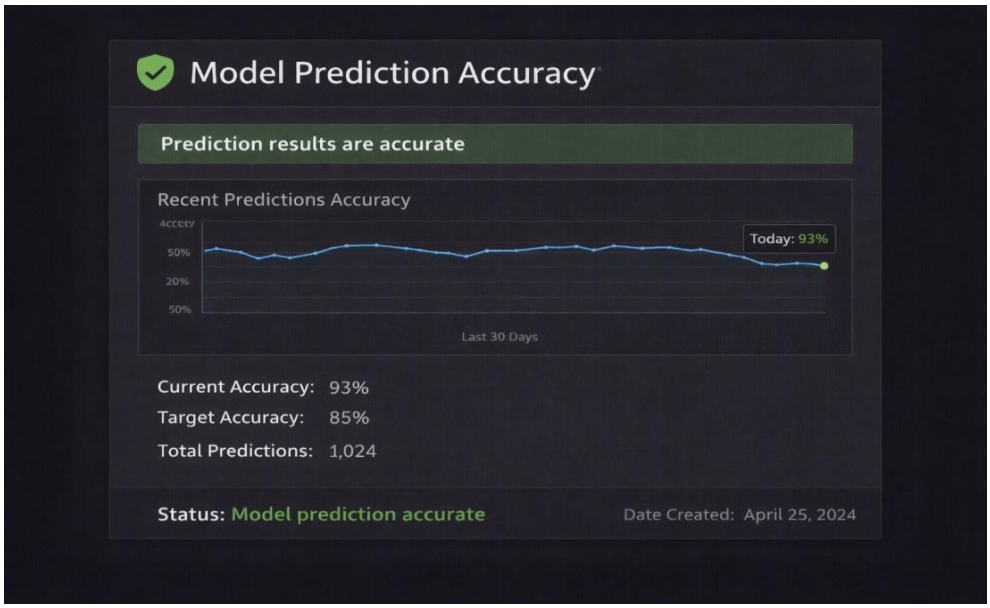


Fig 7.3.5: Normal Input Detection

Description:

This figure shows the classification of a safe input. The system processes a normal query and correctly identifies it as benign, confirming that it can distinguish between safe and malicious inputs.



Description:

This figure displays the performance of the machine learning model in terms of prediction accuracy. It highlights that the model provides reliable and accurate results when analyzing different types of inputs.

8. OUTPUT SCREENS

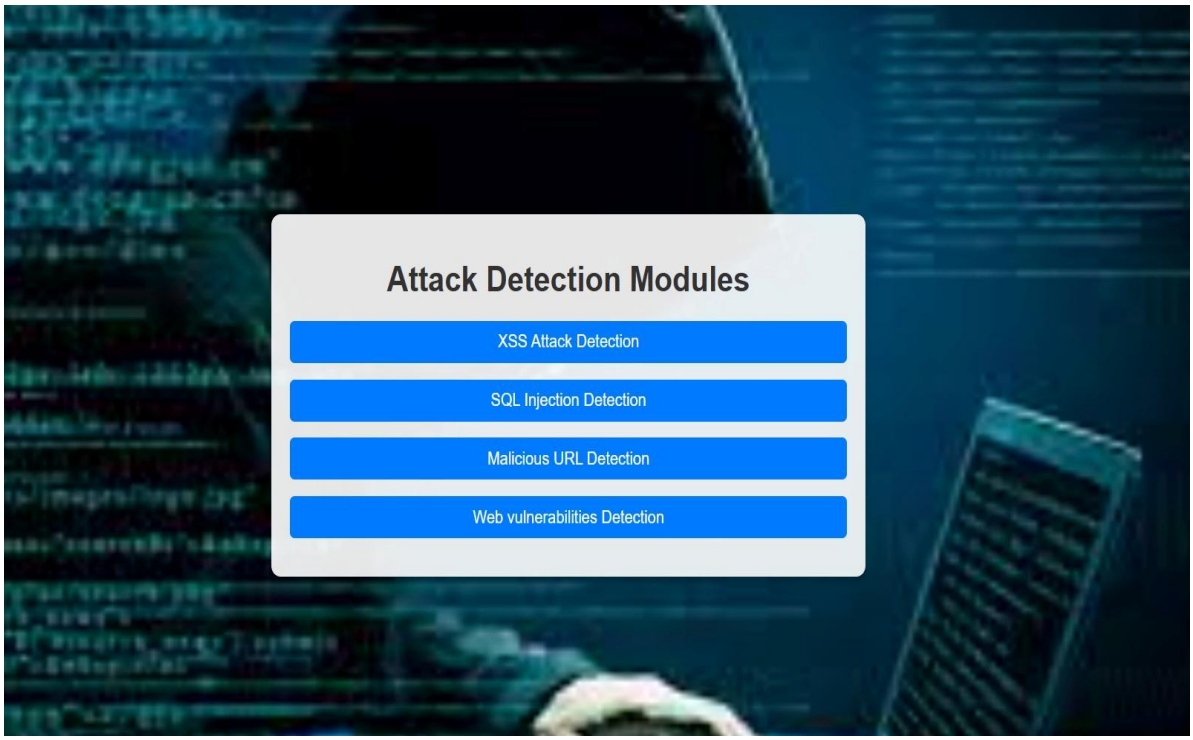


Fig 8.1 Attack Detection Modules Interface

This screen represents the main interface of the system, where different detection modules are available for user selection. It includes options such as XSS Attack Detection, SQL Injection Detection, Malicious URL Detection, and Web Vulnerabilities Detection. This modular design allows users to choose the specific type of threat they want to analyze. The interface is user-friendly and visually structured, ensuring easy navigation between different functionalities. This screen highlights the system's flexibility and scalability in handling multiple types of cyber security threats within a single platform.

In addition, the centralized dashboard improves user interaction by providing quick access to all modules in one place. It reduces complexity and enhances usability for both technical and non-technical users. The modular architecture also allows easy integration of additional security features in the future. This makes the system adaptable to evolving cyber threats.

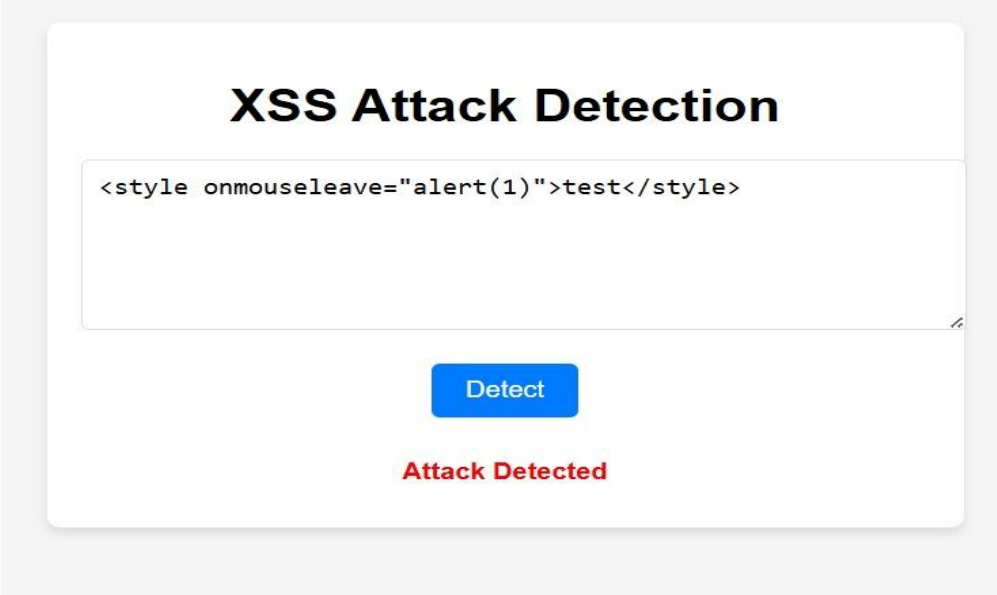


Fig 8.2 XSS Attack Detection Output

This output screen represents the detection of a Cross-Site Scripting (XSS) attack using the developed system. The user provides an input script containing potentially harmful code, such as embedded JavaScript or event-based execution functions like onmouseleave="alert(1)". After processing the input through preprocessing, feature extraction, and the trained machine learning model, the system identifies the script as malicious. The result is clearly displayed as “Attack Detected” in red color, indicating a high-risk input. This output demonstrates the system’s ability to accurately identify harmful scripts that can execute unauthorized actions in a web browser, thereby preventing security breaches and protecting user data.

Additionally, the system analyzes both syntax patterns and behavioral indicators within the script to improve detection accuracy. It ensures that even slightly modified or obfuscated scripts can be detected effectively. This enhances the robustness of the system against real-world attack scenarios. The clear output also helps users quickly understand the severity of the threat and take immediate action.

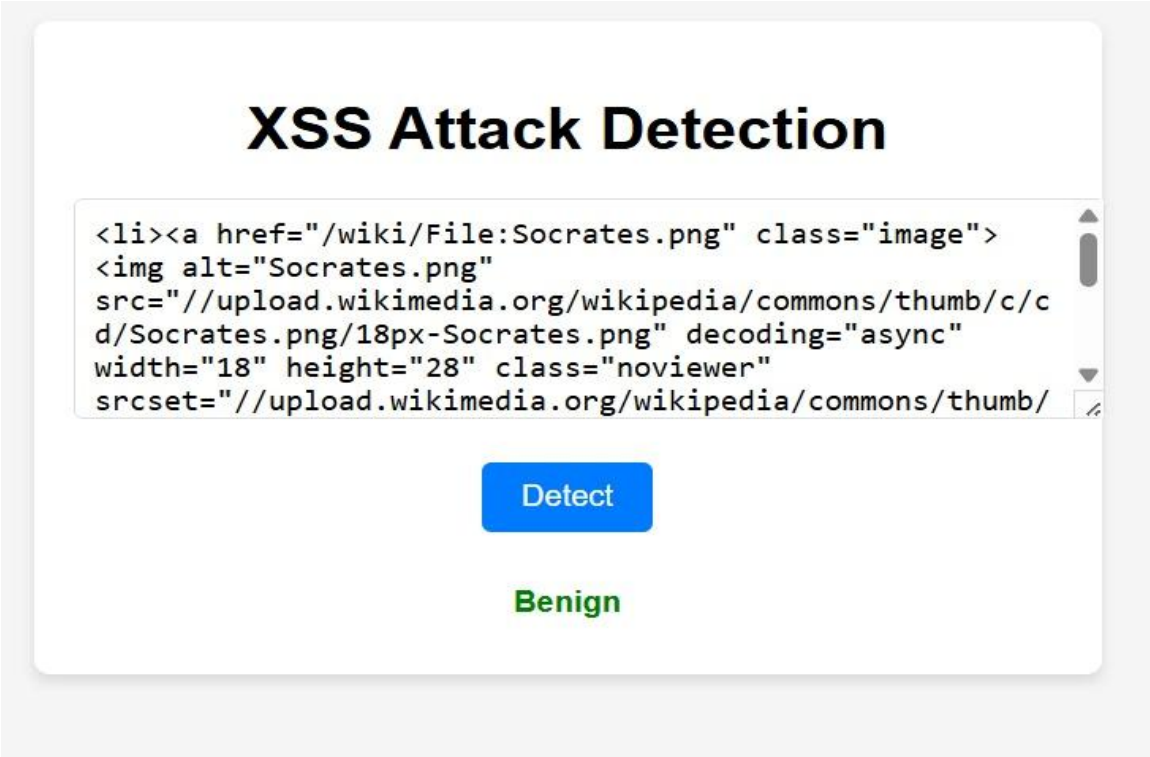


Fig 8.3 XSS Attack Detection Output (Result)

This output screen illustrates a scenario where the system processes a given script input and classifies it as safe or non-malicious. The input may contain HTML elements or structured content but does not include any harmful or executable scripts. After analyzing the input through the detection model, the system labels it as “Benign”, displayed in green color. This confirms that the system not only detects attacks but also correctly distinguishes normal inputs, reducing false positives. It ensures reliability and prevents unnecessary alerts for harmless data.

Furthermore, the system evaluates multiple features such as script structure, keyword patterns, and context before making a decision. This multi-level analysis increases confidence in classification results. By accurately identifying safe inputs, the system maintains usability while ensuring security. This balance is essential for real-time applications.

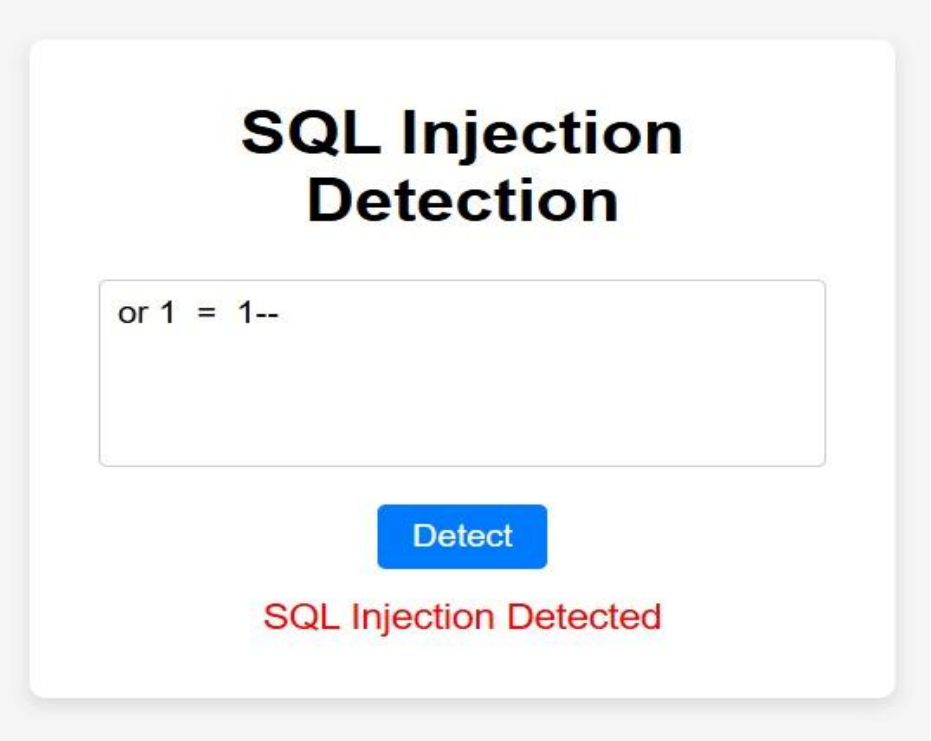


Fig 8.4 SQL Injection Detection Output

This screen shows the detection of a SQL Injection attack. The input query contains suspicious patterns such as OR 1=1--, which are commonly used to bypass authentication and manipulate database queries. The system processes the input and identifies it as malicious, displaying the result as "SQL Injection Detected" in red color. This output proves the system's effectiveness in identifying known attack signatures and preventing unauthorized database access, thereby enhancing system security.

Additionally, the model detects logical anomalies and unusual query structures that indicate malicious intent. It can identify both simple and advanced injection attempts, including obfuscated queries. This improves the system's capability to handle real-world attacks. The clear output helps administrators take immediate preventive measures.

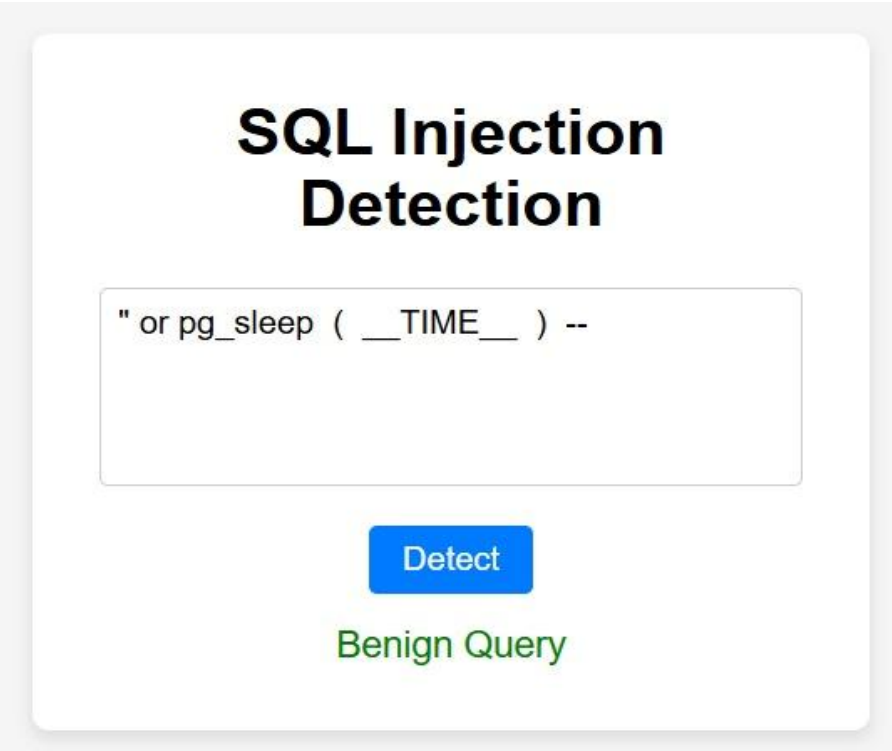


Fig 8.5 SQL Injection Detection Output

This output screen demonstrates the system's ability to analyze SQL queries and classify safe inputs correctly. The provided query may appear complex but does not contain malicious patterns intended to manipulate database operations. After processing through the SQL detection model, the system identifies it as a "Benign Query", displayed in green. This confirms that the model effectively avoids false alarms and accurately differentiates between normal database queries and malicious injections. It ensures that legitimate operations are not interrupted.

Moreover, the system evaluates query structure, syntax, and logical conditions to ensure accurate classification. This prevents misclassification of valid queries that resemble attack patterns. The ability to correctly identify safe queries improves system reliability and user trust. It also supports smooth functioning of database-driven applications.

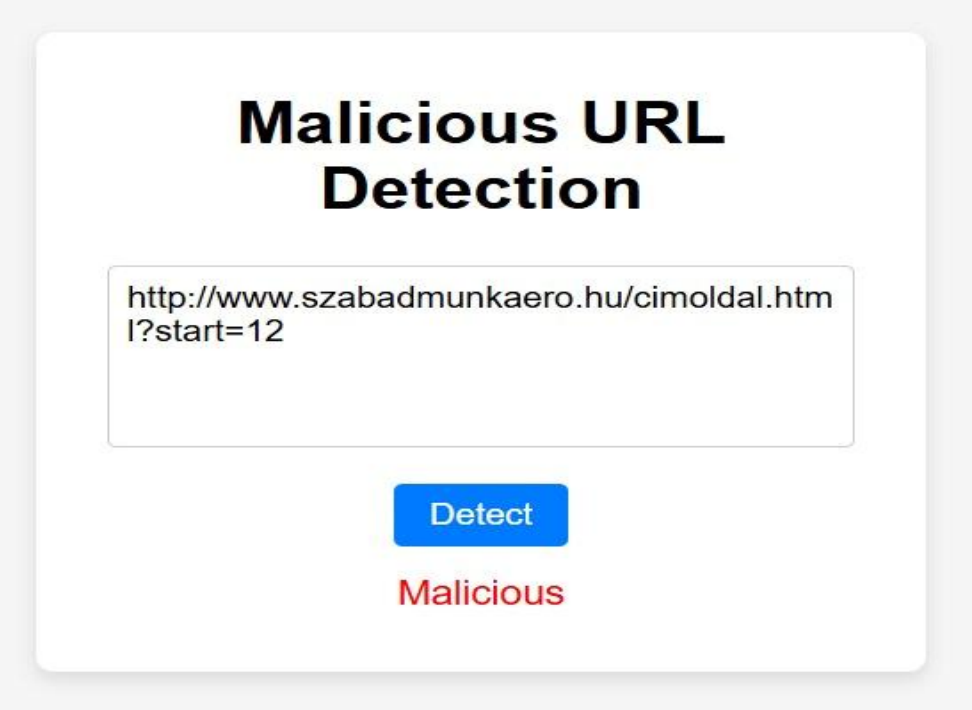


Fig 8.6 Malicious URL Detection Output

This output screen represents the detection of harmful or suspicious URLs. The input URL may contain unusual patterns, redirects, or phishing-related structures. After analysis using the trained model, the system classifies the URL as “Malicious”, displayed in red. This helps in identifying phishing websites or unsafe links that could compromise user data. The output demonstrates the system’s capability to protect users from web-based threats by accurately classifying URLs.

Furthermore, the system evaluates multiple features such as domain characteristics, URL length, special characters, and redirection behavior. This enables detection of both known and unknown malicious URLs. The model also adapts to evolving phishing techniques through learning mechanisms. This ensures continuous improvement in detection accuracy and security.

9. CONCLUSION

The project “Defense Strategies for Epidemic Cyber Security Threats: Modeling and Analysis using a Machine Learning Approach” successfully presents an effective solution for detecting and analyzing cyber threats. The system uses machine learning techniques to identify attacks such as SQL Injection, Cross-Site Scripting (XSS), and malicious URLs by learning patterns from the data. This approach improves accuracy and reduces the limitations of traditional security methods, which are often unable to detect new and evolving threats.

The implementation of data preprocessing, feature extraction, and model training ensures that the system can handle large datasets and provide reliable results. The use of multiple machine learning algorithms enhances the detection capability and allows the system to adapt to different types of cyber threats. The system is also designed to process inputs in real time, which helps in early detection and prevention of attacks. This real-time capability is particularly important in modern network environments where threats spread rapidly and require immediate response.

In addition, the integration of an epidemic-based modeling approach provides a deeper understanding of how cyber threats propagate across interconnected systems. By modeling attacks in a structured manner, the system can identify vulnerable points in the network and support the development of proactive defense strategies. This not only improves detection but also helps in controlling and minimizing the spread of attacks.

The project demonstrates that machine learning can play a significant role in improving cyber security by providing automated and data-driven solutions. It reduces manual effort, minimizes human errors, and increases efficiency in identifying threats. The system is scalable and flexible, allowing it to be extended with advanced algorithms such as deep learning models, ensemble techniques, and real-time monitoring tools in the future.

Furthermore, the system can be enhanced by integrating threat intelligence feeds, cloud-based deployment, and continuous learning mechanisms to improve accuracy over time. It can also be applied in various domains such as web applications, enterprise networks, and IoT environments to strengthen overall security infrastructure.

Overall, the project achieves its objective of developing a reliable, scalable, and efficient system for detecting and analyzing cyber threats. It provides a strong foundation for future research and development in intelligent cyber security systems and contributes significantly to enhancing the security of modern network environments.

10. FUTURE ENHANCEMENTS

The proposed system can be further improved by incorporating advanced machine learning and deep learning techniques to increase accuracy and performance. Algorithms such as deep neural networks and ensemble models can be used to enhance detection capability for more complex and evolving cyber threats. The system can also be extended to handle additional types of attacks beyond SQL Injection, XSS, and malicious URLs.

Another possible enhancement is the integration of real-time monitoring systems that continuously analyze network traffic and detect threats instantly. This will improve the response time and provide better protection against fast-spreading attacks. The system can also be connected with cloud platforms to handle large-scale data and improve scalability.

The user interface can be improved to provide better visualization of results, such as graphical reports and dashboards. This will help users understand system performance and threat patterns more easily. Adding automated alert systems like email or notifications can further enhance usability.

In addition, the system can be updated regularly with new datasets to improve learning and adapt to emerging cyber threats. Security features such as encryption and secure authentication can also be added to protect user data.

Overall, these enhancements will make the system more robust, scalable, and effective in handling modern cyber security challenges.

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