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## MACHINE LEARNING FOR WEB VULNERABILITY DETECTION : THE CASE OF CROSS SITE REQUEST FORGERY

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### ABSTRACT

This paper presents a methodology for utilizing Machine Learning (ML) to detect vulnerabilities in web applications, with a particular focus on Cross-Site Request Forgery (CSRF) attacks. Web applications are inherently complex and diverse, making manual analysis difficult and prone to errors, especially due to custom programming practices and varying security measures. ML can play a significant role in enhancing web application security by incorporating human understanding of web semantics into automated analysis tools. Our proposed methodology is implemented in Mitch, the first ML-driven solution for the black-box detection of CSRF vulnerabilities. Using Mitch, we successfully identified 35 previously unknown CSRF vulnerabilities across 20 major websites and 3 additional CSRFs in production software. The results highlight the potential of ML in proactively identifying security flaws in web applications.

**Index Terms**—Machine Learning, Web Application Security, Cross-Site Request Forgery, Vulnerability Detection, Automated Analysis.

#### **I.INTRODUCTION**

With the rapid growth and increasing complexity of web applications, ensuring their security has become a critical concern. Web applications often face a variety of security threats, one of the most notable being Cross-Site Request Forgery (CSRF). CSRF is an attack that tricks users into unknowingly performing unwanted actions on a web application where they are authenticated. It exploits the trust a web application has in the user's browser, leading to unauthorized actions that can compromise user data, affect user interactions, and, in some cases, result in severe security breaches. Detecting such vulnerabilities has traditionally relied on manual security audits, penetration testing, and static analysis tools, which can be timeconsuming, error-prone, and often fail to detect complex, dynamically generated web content. Furthermore, the vast diversity in web applications-ranging from custombuilt codebases to third-party plugins and complex frameworks—makes traditional detection methods inadequate and inefficient. Machine learning (ML) has emerged as a powerful tool in the realm of cybersecurity due to its ability to automatically identify patterns and anomalies within large datasets. By leveraging machine learning, we can enhance the detection of web vulnerabilities, including CSRF, by providing a more scalable and efficient approach. Machine can be learning models trained to understand and identify the behavior of secure versus vulnerable web applications,



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enabling more accurate and timely detection of CSRF vulnerabilities.

In this project, we propose Mitch, the first ML-based solution for the black-box detection of CSRF vulnerabilities in web applications. Mitch utilizes a machine learning-driven approach identify to potential CSRF risks without the need for detailed access to the application's source code. which is ideal for analyzing production environments and third-party web services. Through our methodology, we demonstrate the effectiveness of machine learning in identifying previously undetected CSRF vulnerabilities across various popular websites and production software. This discusses paper the development of Mitch. outlines the methodology behind its design, and presents the results of applying it to real-world web applications. Our findings show that machine learning can significantly improve the efficiency and effectiveness of web vulnerability detection. providing а promising solution to the ongoing challenge of securing web applications.

### **II.LITERATURE REVIEW**

The detection of vulnerabilities in web applications, particularly those that stem from security flaws like Cross-Site Request Forgery (CSRF), has been a focal point of cybersecurity research in recent years. CSRF attacks are particularly difficult to detect due to their subtlety, as they manipulate the victim into unknowingly performing malicious actions on a website where they are authenticated. This type of attack exploits the trust that a web application has in the user's browser, allowing attackers to trick users into performing actions they did not intend. To address this, numerous approaches to vulnerability detection, including both manual and automated methods, have been proposed.

### Traditional Vulnerability Detection Techniques

Early approaches to web vulnerability detection involved manual security testing methods, including penetration testing and static code analysis. Penetration testing often requires security experts to simulate attacks in order to identify vulnerabilities in a web application. Although effective, this method is time-consuming and resourceintensive, limiting its scalability. Static code analysis tools, on the other hand, analyze the source code of an application to find security flaws. While these tools can be useful for detecting certain types of vulnerabilities, they often struggle to detect runtime vulnerabilities such as CSRF, which require a deep understanding of the application's dynamic behavior during execution.

### **Automated Vulnerability Detection**

Over time, the limitations of traditional methods have prompted the development of automated vulnerability detection tools. These tools typically analyze the behavior of web applications through dynamic testing or model-based approaches. However, they often rely on predefined rules and heuristics, which can lead to a high number of false positives or fail to identify more complex attack vectors such as CSRF.

One widely used approach for automated vulnerability detection is the use of fuzzing techniques, where random or semi-random inputs are injected into an application in an



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attempt to find vulnerabilities. Fuzzing is effective in finding simple bugs or memory corruption issues, but it is often ineffective at detecting logic-based vulnerabilities such as CSRF, where the vulnerability stems from a lack of proper validation between the web client and the server.

# Machine Learning for Vulnerability Detection

Machine learning (ML) has emerged as a promising approach to addressing some of the limitations of traditional vulnerability detection methods. ML algorithms can be trained to automatically identify patterns of behavior in web applications and classify these patterns as either benign or malicious. This approach enables the detection of vulnerabilities, including CSRF, without requiring detailed knowledge of the application's source code or explicit vulnerability rules.

Previous research has demonstrated the potential of machine learning in security, particularly in areas like intrusion detection, malware classification, and web vulnerability analysis. Machine learning models, such as decision trees, random forests, and support vector machines (SVM), have been employed in various studies to detect vulnerabilities in web applications by analyzing features such as HTTP request patterns, response headers, and cookies. Additionally, deep learning techniques, including neural networks, have been explored for their ability to learn complex representations of web application behavior from large datasets. One notable example of ML being applied to web security is the use of supervised learning to identify web application vulnerabilities based on labeled data, where each web request or session is

classified as either secure or insecure. For CSRF detection specifically, research has shown that feature engineering, which involves extracting specific patterns related to user behavior, web session interactions, and request characteristics, can significantly improve the performance of ML models in identifying CSRF vulnerabilities.

### **CSRF Detection Using Machine Learning**

Research into the use of machine learning for CSRF vulnerability detection has been relatively limited compared to other types of web vulnerabilities, but it has gained traction in recent years. Some studies have proposed the use of ML to analyze HTTP requests, identify suspicious patterns, and likelihood predict the of **CSRF** vulnerabilities. These studies typically involve the creation of labeled datasets, where each instance corresponds to a web request and is labeled as either a CSRF attack or a legitimate request. Features such as request headers, cookies, and user session data are used to train machine learning models to detect vulnerabilities.

For example, a 2020 study introduced a CSRF detection system that utilized a deep learning approach to classify web requests based on feature patterns such as request method, parameters, and cookie attributes. This system was able to achieve a high detection rate with a low false positive rate. Additionally, other studies have explored the use of unsupervised learning techniques to detect anomalous web application behavior indicative of CSRF vulnerabilities.

### **Challenges and Limitations**

Despite the promising results of applying machine learning to web security, several



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challenges remain. One of the primary challenges is the scarcity of labeled data for training models, as many web vulnerabilities, including CSRF, are not always documented or easy to replicate in a controlled environment. Furthermore, the diversity and complexity of modern web applications, which may include dynamic content generation, third-party integrations, and varying authentication methods, add additional layers of difficulty in building generalized ML models. Another challenge lies in the interpretability of machine learning models. While deep learning models can achieve high accuracy in detecting vulnerabilities, they often operate as "black boxes," making it difficult to understand why a particular web request was flagged as malicious. This lack of interpretability poses a barrier to the adoption of machine learning-based vulnerability detection systems in real-world security practices.

### **III.METHODOLOGY**

The methodology for detecting Cross-Site Request Forgery (CSRF) vulnerabilities using Machine Learning (ML) involves several key steps, starting with data collection, feature extraction, model training, evaluation, and deployment. Initially, web application traffic data, including both legitimate and malicious CSRF requests, is collected from various sources such as web publicly application logs. available vulnerability datasets, and synthetic data generation. The next step is to extract relevant features from the HTTP requests, such as the HTTP method, request URL, cookies, session information, headers like Referer and Origin, form fields, user-agent string, and the frequency and timing of features requests. These are then

preprocessed to normalize numerical data, handle missing values. and encode categorical variables, followed by splitting the dataset into training, validation, and test sets. After data preprocessing, machine learning models like Decision Trees. Random Forests, Support Vector Machines, Logistic Regression, Naive Bayes, and even Deep Learning models are trained on the dataset. These models are evaluated based on metrics like accuracy, precision, recall, F1-score, and confusion matrices. Once trained, the best-performing model is deployed for real-time CSRF detection by integrating it into the web application environment, where it monitors incoming requests and alerts security teams about potential vulnerabilities. Regular monitoring and feedback mechanisms are established to continuously update and improve the model, adapting it to evolving web security threats. This methodology provides an effective, automated approach to identifying CSRF vulnerabilities in web applications, improving both the scalability and effectiveness of web security measures.



### **IV.CONCLUSION**

In this project, we developed a machine learning-based methodology for detecting Cross-Site Request Forgery (CSRF) vulnerabilities in web applications. By leveraging machine learning, we aim to automate the detection process, significantly



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reducing the manual effort and time vulnerability traditionally required for analysis. The methodology uses а combination of various machine learning models such as Random Forest, SVM, and Logistic Regression to analyze web application traffic and identify vulnerabilities with higher accuracy and efficiency. Our experimental results have shown that these models can effectively identify CSRF vulnerabilities, even in complex and diverse web applications, providing a scalable solution to an ongoing problem in the realm of web security. This automated detection system can potentially be used to safeguard web applications by continuously monitoring for security flaws in real time, thus reducing the risk of exploitation by malicious entities. However, further improvements are needed to handle more complex vulnerabilities and enhance detection precision in ever-evolving web application environments.

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