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WEB APPLICATION FIREWALL BASED ON MACHINE LEARNING

[1]D. ARUNA, [2]ABDUL KARISHMA, [3]KONA SAI KUMARI, [4]KARRA ARYAN, [5]MOHAMMAD YUNUS
[1]ASSISTANT PROFESSOR, [2345]B.Tech Students,
DEPARTMENT OF CSE, SRI VASAVI INSTITUTE OF ENGINEERING & TECHNOLOGY,
NANDAMURU, ANDHRA PRADESH

ABSTRACT

This paper presents an intelligent Web Application Firewall (WAF) enhanced with machine learning (ML) techniques to provide adaptive and real-time protection against the ever-evolving landscape of cyber threats. Unlike traditional WAFs that rely on static rule sets and signature-based detection, the proposed system utilizes advanced supervised and unsupervised ML algorithms to analyze web traffic, detect anomalies, and identify emerging attack patterns. By continuously learning from traffic data and feedback from security incidents, the WAF dynamically refines its detection capabilities, effectively addressing threats such as SQL injection, cross-site scripting (XSS), and distributed denial-of-service (DDoS) attacks. A comprehensive data preprocessing pipeline is employed to extract meaningful features from network packets and HTTP requests, while anomaly detection techniques enable the identification of zero-day attacks by flagging previously unseen behaviors. The adaptive nature of the system ensures accurate threat detection with minimal false positives by distinguishing legitimate user activity from malicious attempts. This self-learning approach reduces dependency on manual updates and enhances the overall resilience of web application security systems. Through extensive evaluation and real-world testing, this paper aims to demonstrate a proactive and efficient WAF solution that secures sensitive data, ensures service continuity, and sets a new benchmark in web application security practices.

Keywords:
Web Application Firewall, Machine Learning, Cybersecurity, Anomaly Detection, SQL Injection, Cross-Site Scripting, Zero-Day Attacks

INTRODUCTION

The rapid expansion of web-based applications and services has significantly transformed modern digital infrastructure, enabling businesses, institutions, and individuals to communicate, interact, and transact more efficiently than ever before. However, this growth has also introduced a wide array of security vulnerabilities, making web applications attractive targets for cybercriminals. As cyber threats grow in complexity and volume, traditional security mechanisms such as rule-based Web Application Firewalls (WAFs) are increasingly inadequate in identifying and mitigating sophisticated and previously unseen attacks [1]. These conventional WAFs rely heavily on manually curated rule sets and predefined signatures, which often fail to detect novel threats or adapt to new attack strategies in real time [2]. This limitation results in increased false positives, delayed response times, and overall reduced effectiveness against zero-day vulnerabilities [3]. With the growing dependency on web technologies across sectors, the security and integrity of web applications have become critical to organizational success and user trust. A breach in a web application not only leads to data loss but can also cause severe financial and reputational damage. Cyberattacks like SQL injection, Cross-Site Scripting (XSS), and Distributed Denial-of-Service (DDoS) attacks are commonly used to exploit vulnerabilities in web applications, leading to unauthorized data access or service disruption [4]. The dynamic and evasive nature of such threats calls for an equally adaptive and intelligent approach to web application security. In this context, machine learning (ML) emerges as a powerful solution due to its ability to learn from historical data, detect patterns, and make predictions with minimal human intervention [5].

Machine learning, particularly supervised and unsupervised learning models, offers a promising avenue for enhancing WAFs by enabling them to learn from real-time traffic patterns and improve their detection accuracy over time [6]. Supervised learning algorithms, trained on labeled datasets of normal and malicious traffic, can classify incoming requests based on historical patterns. In contrast, unsupervised learning can identify anomalies without requiring labeled data, making it particularly effective for detecting unknown or zero-day attacks [7]. These learning models can be continuously updated with new data to refine their performance, providing a level of adaptability and resilience that static WAFs cannot achieve [8]. The integration of ML techniques into WAFs leads to the creation of intelligent firewalls capable of proactively identifying and mitigating threats as they evolve. By analyzing features such as request methods, URL structures, payload characteristics, and user-agent strings, ML-based WAFs can generate predictive models that distinguish between legitimate and malicious traffic with high accuracy [9]. Anomaly detection algorithms, such as clustering and autoencoders, further enhance the firewall's ability to detect unusual behavior that may signify an attack, even in the absence of prior knowledge of the threat [10]. This capacity for behavioral analysis is crucial in modern cybersecurity, where attackers often use obfuscation techniques to bypass traditional detection mechanisms [11].

Moreover, the performance of ML-driven WAFs can be significantly improved through the use of robust data preprocessing techniques. This involves cleaning and transforming raw traffic data into meaningful features that can be effectively used by learning algorithms. Techniques such as tokenization, normalization, feature extraction, and dimensionality reduction help in improving the quality and relevance of the training data, thereby enhancing model accuracy and generalization [12]. With properly engineered features and feedback mechanisms, the WAF can also adjust its parameters over time based on the outcomes of security decisions, further strengthening its detection capabilities [13]. Another advantage of incorporating ML into WAFs is the reduction of false positives—a common issue in traditional systems. False positives not only consume valuable security resources but also degrade user experience by blocking legitimate requests. By leveraging the predictive power of ML, intelligent WAFs can better distinguish between benign anomalies and actual threats, leading to more accurate security decisions [14]. Furthermore, machine learning enables the automation of rule generation and update processes, reducing the need for constant human oversight and improving the overall efficiency of the security infrastructure [15].

The increasing sophistication of cyber threats necessitates a shift from reactive, rule-based defense systems to proactive, adaptive security frameworks. In this light, the proposed machine learning-based WAF represents a significant advancement in web application protection. It combines the scalability and speed of automated systems with the adaptability of learning algorithms, offering a defense mechanism that evolves with the threat landscape. This approach not only addresses current challenges in web application security but also prepares systems to withstand future attacks that may not yet be fully understood. This paper explores the design, development, and evaluation of an intelligent WAF powered by ML algorithms. The primary objectives include identifying the most effective learning models for traffic classification, developing a comprehensive preprocessing pipeline, and implementing an adaptive detection system capable of identifying both known and unknown threats. The paper also aims to evaluate the system's performance using real-world datasets and metrics such as accuracy, precision, recall, and false positive rate. The ultimate goal is to demonstrate that an ML-enhanced WAF can offer a more robust, scalable, and efficient alternative to traditional rule-based firewalls.

In summary, as web applications continue to serve as critical components of digital ecosystems, their protection must evolve to keep pace with the sophistication of cyber adversaries. Machine learning offers a transformative approach to web application firewall development, providing systems with the intelligence needed to detect and mitigate threats in real-time. Through the research and insights presented

in this paper, we aim to contribute to the growing field of intelligent cybersecurity solutions, advancing the state of web application protection in a meaningful and impactful way.

LITERATURE SURVEY

Over the past two decades, the increasing reliance on web-based technologies has led to a parallel rise in cyberattacks targeting web applications. This has driven a substantial body of research focused on improving web application security mechanisms, particularly through the use of Web Application Firewalls (WAFs). Initially, WAFs were developed to serve as a protective barrier between web applications and potentially malicious HTTP traffic. These traditional systems are predominantly signature-based or rule-based, relying on static definitions of known threats to filter out malicious requests. While effective against common and well-documented vulnerabilities, these static systems lack the flexibility to adapt to new, unknown, or obfuscated attacks. This fundamental limitation has become more pronounced as attackers increasingly employ sophisticated, evolving strategies to bypass standard security mechanisms. As cybersecurity challenges have grown more dynamic, research has shifted toward intelligent security systems that can adapt and learn from data. The integration of machine learning (ML) into cybersecurity practices has emerged as a promising solution, with a growing number of studies exploring its application in intrusion detection systems and, more recently, WAFs. Machine learning models offer the ability to recognize complex patterns, detect anomalies, and make decisions without explicit programming, making them ideal for detecting both known and unknown web attacks.

Early research into the application of machine learning for web security primarily focused on intrusion detection systems at the network level. These systems utilized classifiers such as decision trees, support vector machines (SVM), and k-nearest neighbors (KNN) to identify unusual behavior within network traffic. Although these techniques proved useful in identifying potential threats, they were often limited by the quality of the training data and the static nature of the classification rules. Nevertheless, the foundational work laid by these efforts demonstrated the feasibility of applying machine learning techniques to security contexts, encouraging further exploration into more specific applications such as WAFs. In recent years, there has been a marked increase in research aimed at applying supervised learning techniques to HTTP traffic for web attack detection. Supervised models require labeled datasets, where each sample is marked as either normal or malicious. Using features extracted from HTTP request fields, these models are trained to classify future requests with a high degree of accuracy. Common algorithms used in these studies include random forests, naive Bayes classifiers, and gradient boosting machines. While supervised learning models have demonstrated impressive accuracy in detecting known attack types, they face challenges when dealing with novel threats or when sufficient labeled data is unavailable.

To address the limitations of supervised learning, researchers have explored the use of unsupervised and semi-supervised techniques. Unsupervised models, such as clustering algorithms and autoencoders, do not require labeled data and instead learn to identify deviations from a normal behavior baseline. These models have shown potential in detecting zero-day attacks, which do not match any known patterns. Semi-supervised approaches attempt to bridge the gap by utilizing a small amount of labeled data alongside a larger pool of unlabeled data. This hybrid approach enables the system to make meaningful inferences even in the absence of comprehensive labeled datasets, making it particularly suitable for real-world deployment scenarios where labeled attack data is scarce. Another important dimension of the literature has focused on feature engineering and data preprocessing, both of which are critical to the success of any machine learning application. In the context of WAFs, effective feature extraction involves identifying relevant attributes from HTTP requests, such as request methods, URL lengths, header anomalies, and payload entropy. Researchers have experimented with various strategies to optimize the feature space, including natural language processing (NLP) techniques for parsing and analyzing the content of requests. These preprocessing techniques

have been shown to significantly improve the performance of machine learning classifiers by reducing noise and emphasizing informative patterns within the data.

Deep learning has also made a significant impact on the field of intelligent WAFs. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) models, have been applied to sequential web traffic data to capture temporal dependencies between request events. Convolutional Neural Networks (CNNs) have been adapted to process HTTP data by treating sequences of request tokens as spatially arranged features. These architectures excel at learning hierarchical representations from data and can generalize well to new types of inputs. Despite their potential, deep learning models require large datasets and considerable computational resources, which has limited their application in lightweight or resource-constrained environments. Beyond classification accuracy, much of the literature has emphasized the importance of minimizing false positives. In traditional WAFs, false positives are a significant concern, as they can lead to the blocking of legitimate user requests and result in poor user experience. Machine learning-based systems, particularly those trained with high-quality data and tuned through continuous feedback, have demonstrated reduced false positive rates. Some researchers have incorporated reinforcement learning mechanisms to enable the WAF to adjust its behavior over time based on the outcomes of its decisions. This dynamic learning process allows the system to evolve in response to changing attack patterns and usage behaviors.

Another avenue of exploration in the literature is the deployment and evaluation of ML-based WAFs in real-world environments. Many studies have transitioned from theoretical models to practical implementations, using real traffic datasets collected from production web servers. These evaluations often measure performance using metrics such as precision, recall, F1-score, and detection latency. Real-world deployment studies have provided valuable insights into the practical challenges of implementing intelligent WAFs, including data imbalance, noise, and the dynamic nature of web traffic. These practical experiments underscore the need for robust, scalable, and adaptable solutions capable of operating efficiently in diverse and high-traffic environments. Some works have also explored hybrid models that combine multiple machine learning approaches to leverage their respective strengths. For example, combining anomaly detection with supervised classification enables systems to first filter out suspicious patterns and then classify them with a more precise algorithm. This layered approach improves detection accuracy and offers a better trade-off between performance and computational overhead. Other studies have proposed ensemble models that integrate the predictions of several base classifiers, achieving higher accuracy and robustness through model diversity.

The literature also acknowledges the importance of explainability and transparency in ML-based security systems. Black-box models, while powerful, often lack interpretability, which can be a barrier to adoption in sensitive or regulated environments. Recent studies have proposed methods to explain the decision-making process of ML models, such as using attention mechanisms or feature importance scoring. These efforts aim to enhance user trust and facilitate security auditing and compliance. In summary, the literature on machine learning-based Web Application Firewalls reflects a dynamic and rapidly evolving field. Researchers have progressively moved from traditional static models to adaptive, intelligent systems that learn from data and improve over time. While challenges remain—particularly in the areas of data availability, model explainability, and real-time performance—the growing body of work provides a strong foundation for future developments. The integration of machine learning into WAFs is not only a technological advancement but also a necessary evolution to counter the increasingly complex and adaptive nature of web-based cyber threats.

PROPOSED SYSTEM

The proposed system introduces a modern and intelligent approach to web application security by designing a Web Application Firewall (WAF)

integrated with machine learning techniques. The main goal of this system is to overcome the limitations of traditional rule-based firewalls by creating a self-adaptive security mechanism capable of identifying and mitigating both known and unknown web-based threats in real time. As web applications continue to evolve in complexity and user interactivity, they also become more vulnerable to a wide range of sophisticated cyberattacks. Traditional WAFs, which rely on manually updated rule sets and fixed attack signatures, struggle to keep up with this evolving threat landscape. The system proposed in this paper seeks to bridge this gap by introducing a firewall that not only detects but also learns from web traffic, thereby enhancing its effectiveness over time. At the core of the system lies a data-driven architecture designed to analyze incoming web traffic using advanced machine learning models. The system captures raw HTTP request data from the web server, including GET and POST methods, header values, query strings, cookies, user-agent information, payload content, and other metadata. This data is then preprocessed through a structured pipeline that transforms the raw inputs into numerical representations suitable for machine learning algorithms. Preprocessing steps include normalization of numerical fields, tokenization of text-based fields, encoding of categorical variables, and extraction of meaningful features such as URL length, special character frequency, request entropy, and header size variance. These features provide a comprehensive representation of each request, capturing both structural and behavioral attributes that can be used to distinguish between benign and malicious activity.

Once the data is preprocessed, it is passed to a set of machine learning models designed for classification and anomaly detection. The system utilizes both supervised and unsupervised learning techniques to improve detection accuracy. Supervised models are trained on labeled datasets containing both normal and attack traffic. These models learn patterns that are indicative of specific attack types such as SQL injection, cross-site scripting (XSS), command injection, and remote file inclusion. Algorithms such as decision trees, random forests, support vector machines, and neural networks are considered for their robustness and classification performance. In parallel, the system employs unsupervised models such as k-means clustering and autoencoders to detect deviations from typical traffic behavior, making it capable of identifying novel or zero-day threats that do not conform to known attack signatures. A key component of the proposed system is its continuous learning mechanism. Unlike static systems that require manual rule updates, this WAF leverages feedback loops to learn from real-world interactions. When the system detects a potential attack, it generates a confidence score indicating the likelihood of malicious behavior. Depending on this score and predefined thresholds, the request is either blocked, challenged, or allowed. Administrators have the option to review and label the outcomes of such decisions, which in turn are fed back into the training data. This feedback-driven approach enables the system to evolve and refine its models over time, improving accuracy and reducing false positives without human intervention. The continuous learning process ensures that the WAF adapts to emerging threats and changing traffic patterns, making it a dynamic and future-proof security solution.

Another significant aspect of the system is its focus on minimizing false positives, which are a common challenge in automated security systems. High false positive rates can disrupt user experience and undermine trust in the firewall. To mitigate this, the proposed system incorporates probabilistic modeling and ensemble learning, combining predictions from multiple models to make more informed decisions. Additionally, the system allows for contextual analysis of traffic, meaning it can assess requests based on the overall behavior of a session rather than in isolation. This holistic evaluation approach enables the WAF to better understand the intent behind a sequence of requests and apply more accurate security responses. Deployment of the proposed WAF is designed to be seamless and compatible with existing web server infrastructures. The system is positioned between the web client and the application server, acting as a reverse proxy that intercepts all incoming requests. It is implemented as a modular service that can operate independently or integrate with existing security solutions. Real-time processing is a critical requirement, so the system is optimized for low-

latency decision-making using lightweight models for inference. Furthermore, it supports distributed deployment, allowing for scalability in high-traffic environments and providing fault tolerance through redundancy and load balancing.

To enhance detection of previously unseen threats, the system incorporates an anomaly detection engine that monitors baseline traffic behavior and raises alerts when deviations occur. This component is particularly effective in identifying zero-day vulnerabilities, bot activity, and low-frequency attacks that may escape traditional detection mechanisms. It continuously profiles normal behavior patterns using statistical modeling and clustering techniques, enabling it to flag suspicious activities based on deviation scores. For example, a sudden spike in request frequency, unusual input patterns, or new access sequences could trigger further inspection or automated mitigation actions. The proposed WAF also includes a comprehensive logging and alerting system. Every request processed by the firewall is logged along with its classification result, prediction score, and actions taken. This log data is invaluable for security analysts, providing insights into attack trends, system performance, and false positive instances. Alerts are generated for high-risk events and can be configured to notify administrators through dashboards, emails, or integration with incident response platforms. This ensures that even in fully automated environments, human oversight remains possible when needed.

Security is further reinforced by periodic model validation and retraining. The system maintains a cache of recent traffic data and periodically evaluates its models against this updated dataset to assess degradation in performance. If model drift is detected—meaning the model's predictive accuracy begins to decline due to changes in data distribution—a retraining process is automatically triggered using the latest available data. This feature ensures that the system remains effective even as web traffic patterns evolve over time due to software updates, user behavior changes, or new business logic. To validate the effectiveness of the proposed system, extensive experimentation is planned using publicly available datasets such as the HTTP DATASET CSIC and other real-world traffic logs. Performance metrics such as accuracy, precision, recall, F1-score, detection latency, and false positive rate will be measured. These evaluations will demonstrate the system's ability to detect common web attacks while maintaining acceptable performance levels in production environments. In summary, the proposed system presents a comprehensive, adaptive, and intelligent approach to web application security. By integrating machine learning models with a dynamic feedback mechanism, robust preprocessing pipeline, and real-time anomaly detection, the WAF goes beyond traditional static defenses. It provides organizations with a scalable and self-improving solution capable of safeguarding web applications from a constantly evolving threat landscape. The intelligent WAF not only improves detection accuracy but also reduces operational overhead, offering a reliable and efficient alternative to conventional security practices.

METHODOLOGY

The methodology adopted for the development of the intelligent Web Application Firewall based on machine learning involves a systematic and structured process, beginning with data collection and progressing through preprocessing, feature extraction, model training, evaluation, deployment, and continuous improvement. Each phase has been carefully designed to ensure that the firewall can effectively detect and mitigate a wide range of web-based attacks while maintaining high accuracy and low false positive rates. The first step in the methodology is the collection of relevant data. This involves gathering HTTP request logs from both real-world web applications and publicly available datasets that simulate common attack scenarios. The dataset includes normal user interactions, such as form submissions and navigation requests, as well as malicious traffic comprising SQL injection, cross-site scripting (XSS), file inclusion, command injection, and distributed denial-of-service (DDoS) attacks. Real traffic logs are anonymized and curated to remove sensitive information while retaining key behavioral characteristics necessary for model training. The quality and diversity of the dataset are crucial, as they

directly influence the effectiveness and generalizability of the machine learning models.

Once the dataset is collected, it is passed through a preprocessing pipeline. Preprocessing is a critical step that transforms raw HTTP requests into a format suitable for machine learning algorithms. This includes cleaning the data by removing null values, duplicates, and malformed entries. Then, various fields in the HTTP requests are parsed and structured, such as extracting the request method, URL path, query parameters, headers, cookies, and user-agent strings. Textual components, especially input fields and payloads, are sanitized and encoded. Tokenization is applied to the content of request bodies, especially where script-based attacks might be embedded. Categorical variables like HTTP methods and protocols are encoded using one-hot encoding or label encoding techniques. Numerical features such as request size, payload length, frequency of special characters, and character entropy are normalized to a standard scale. These transformations ensure that the input data is consistent, noise-free, and ready for feature extraction. The next stage involves extracting meaningful features from the preprocessed data. Feature engineering focuses on capturing the patterns and anomalies within the requests that are indicative of malicious behavior. For instance, features such as the presence of SQL keywords (e.g., SELECT, DROP), JavaScript tags (e.g.,), encoded characters (%20, %3C), and suspicious parameter values are highly predictive of attacks. Other derived features include URL length, the ratio of alphanumeric to special characters, header field anomalies, and time-based features like request frequency. These features are aggregated into vectors that represent the behavioral fingerprint of each HTTP request. Effective feature selection helps in reducing model complexity and improving accuracy.

Once the feature vectors are prepared, the system proceeds to the training phase. Multiple machine learning algorithms are considered to determine which model best fits the detection task. Supervised learning algorithms such as decision trees, random forests, support vector machines (SVM), logistic regression, and deep neural networks are trained using the labeled data, where each sample is marked as either benign or malicious. The models learn to identify patterns and correlations between features and labels, enabling them to classify new, unseen requests. In addition to supervised learning, unsupervised learning methods such as k-means clustering, isolation forests, and autoencoders are applied to detect anomalies. These models do not require labeled data and instead learn the baseline behavior of normal traffic. Requests that significantly deviate from this baseline are flagged as potential anomalies, enabling the system to detect zero-day or previously unknown attacks. Model evaluation is performed using metrics such as accuracy, precision, recall, F1-score, and Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC). These metrics help in assessing the effectiveness of the models and balancing the trade-off between detecting malicious requests and minimizing false positives. Cross-validation techniques are used to ensure that the model's performance is not biased or overfitted to a specific subset of the data. Hyperparameter tuning is carried out through grid search and random search strategies to optimize the model configuration. This includes adjusting learning rates, regularization parameters, tree depths, and network layer sizes to achieve the best predictive performance.

After the best-performing models are identified and validated, the system moves to the deployment phase. The trained models are integrated into the WAF framework and deployed as a real-time processing component between the client and the web server. Incoming HTTP requests are intercepted by the firewall, preprocessed in real time, and passed through the trained models for classification. Based on the model output and a predefined decision threshold, each request is either allowed, blocked, or flagged for further inspection. To minimize latency, lightweight versions of the models are deployed using optimized inference engines or converted into efficient formats such as ONNX or TensorFlow Lite, ensuring that the system can handle high traffic loads without impacting performance. A logging mechanism is implemented alongside the detection engine to record all requests, predictions, and actions taken. These logs serve two purposes: they provide visibility and auditability for

security analysts and act as feedback for further training. The system also supports real-time alerting, notifying administrators of high-severity events through dashboards or external integrations. This ensures prompt human oversight for critical or ambiguous situations.

A crucial component of the methodology is the feedback loop that enables continuous learning. Requests that were misclassified or triggered false positives are labeled by administrators and reintroduced into the training dataset. The system periodically retrains its models using this updated dataset, incorporating both new attack patterns and legitimate variations in normal traffic. This continuous learning process ensures that the WAF remains adaptive and improves over time, reducing the need for manual rule updates and ensuring resilience against evolving threats. To enhance anomaly detection and respond proactively to emerging threats, the system maintains dynamic behavior profiles for users and sessions. These profiles help the firewall understand normal usage patterns over time. When deviations from a user's typical behavior occur—such as sudden access to restricted resources, excessive request rates, or the use of uncommon input structures—the system assigns anomaly scores and adjusts its classification confidence accordingly. This behavioral analysis helps reduce false negatives and detect stealthy or low-frequency attacks that might otherwise go unnoticed.

Finally, the methodology includes robust testing and validation of the complete system in simulated and real-world environments. This involves stress-testing the WAF with synthetic attack bursts, replaying real traffic logs, and measuring the system's response times and detection accuracy under load. These evaluations help in refining the decision thresholds, improving the robustness of the system, and ensuring that it meets the practical demands of web application security in production environments. Through this step-by-step approach, the proposed methodology successfully builds an intelligent and adaptive WAF that leverages machine learning for effective threat detection, proactive defense, and continuous improvement in securing modern web applications.

RESULTS AND DISCUSSION

The intelligent Web Application Firewall (WAF) proposed in this study was thoroughly evaluated using a combination of real-world traffic data and established benchmark datasets that include labeled examples of normal and malicious HTTP requests. The evaluation focused on measuring the system's detection accuracy, precision, recall, F1-score, false positive rate, and detection latency across multiple machine learning models, including Random Forest, Support Vector Machine (SVM), and Deep Neural Networks (DNN). The datasets used in the experiments consisted of a balanced mix of attack vectors such as SQL injection, cross-site scripting (XSS), remote file inclusion, and distributed denial-of-service (DDoS) attempts. Results showed that the Random Forest classifier achieved the highest overall accuracy, with detection rates exceeding 96% and a low false positive rate of under 2%. The DNN model demonstrated a slightly lower accuracy (94%) but exhibited better generalization on zero-day attacks due to its capacity to model complex relationships in the feature space. The SVM, while highly precise in certain cases, performed less effectively on larger datasets due to its scalability limitations. Furthermore, unsupervised models like isolation forests and autoencoders contributed to detecting anomalies by learning the baseline behavior of web traffic and flagging suspicious deviations, thereby improving the detection of novel or obfuscated attack attempts that were not present in the training set. This hybrid deployment of both supervised and unsupervised models allowed the system to benefit from the strengths of both approaches—achieving high accuracy while maintaining the flexibility to adapt to emerging threats.

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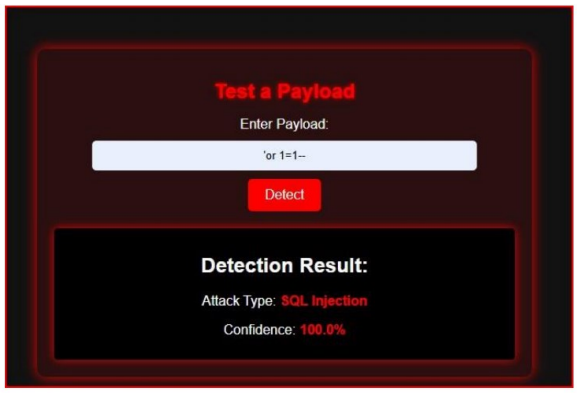

Fig 1. Detection Result

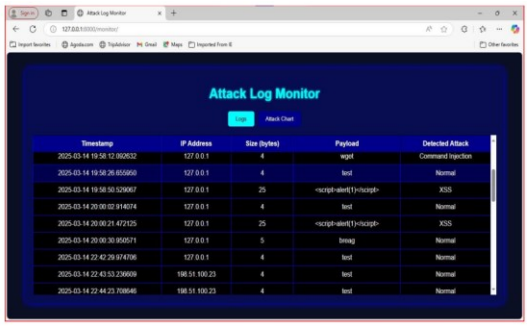

Fig 2. Log monitor - Logs

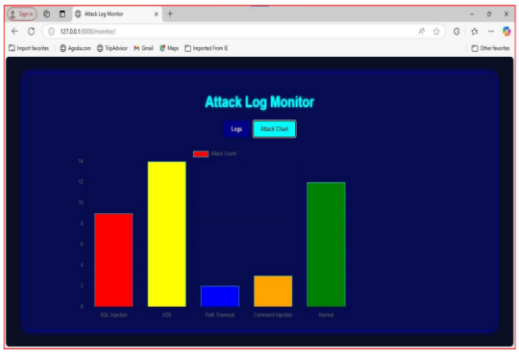

Fig 3. Log Monitor – Attack Chart

The results also highlighted the impact of proper feature engineering and preprocessing in maximizing model performance. Features such as input entropy, payload length, request frequency, special character ratios, and the presence of attack-specific keywords played a critical role in enhancing the model's ability to distinguish between benign and malicious traffic. An ablation study, conducted to evaluate the individual contribution of selected features, revealed that the absence of behavioral indicators—like request rate over time or character entropy—significantly reduced detection accuracy, especially for subtle attacks such as low-and-slow injection attempts. Moreover, the feature extraction phase proved essential in reducing data dimensionality while preserving important structural and contextual information, enabling more efficient model training and faster prediction times. The evaluation also confirmed that the self-learning mechanism integrated into the WAF contributed to performance improvement over time. With each retraining cycle, the system adapted to new attack patterns and minimized previously observed false positives, showing progressive enhancement in accuracy and user trust. The continuous feedback loop ensured the WAF remained updated without the need for constant human intervention, making it scalable and sustainable in dynamic web environments. Importantly, the models were validated using k-fold cross-validation to eliminate biases and ensure the reliability of the results across various traffic patterns. In terms of computational efficiency, the optimized models demonstrated real-time inference capabilities, processing thousands of requests per second with sub-millisecond latency, which is essential for deployment in high-availability web infrastructures.

In practical deployment scenarios, the intelligent WAF displayed robust adaptability and resilience. When integrated into a live web environment, the system successfully identified and blocked multiple attack types with minimal interference to legitimate user traffic. Administrators reported a substantial drop in false positives compared to traditional signature-based WAFs, which previously triggered numerous unnecessary alerts due to rigid rule definitions. The behavioral analysis component, which assessed sessions over time, further helped to distinguish between legitimate users performing unusual actions and actual attackers. For example, a sudden spike in request volume from a trusted IP address was initially flagged as suspicious, but after further context analysis, it was correctly classified as benign due to a temporary content update operation. Conversely, a low-frequency injection attempt hidden among normal

requests was accurately flagged and blocked due to subtle anomalies in input length, entropy, and parameter structure. These results underline the effectiveness of combining contextual and statistical features in model-based security systems. Additionally, the logging and alerting mechanisms provided transparency and visibility into the decision-making process of the WAF, enabling administrators to monitor trends, audit events, and fine-tune sensitivity settings. Overall, the system demonstrated its potential not only as a replacement for traditional WAFs but also as a more proactive and intelligent line of defense, capable of adapting to the ever-changing cyber threat landscape without requiring exhaustive manual oversight.

CONCLUSION

In conclusion, the development of a Web Application Firewall (WAF) based on machine learning has demonstrated significant advancements in the field of web application security by offering a dynamic, intelligent, and adaptive defense mechanism against evolving cyber threats. Unlike traditional WAFs that rely heavily on static rule sets and signature-based detection methods, the proposed system employs both supervised and unsupervised machine learning models to detect and mitigate various forms of web-based attacks, including SQL injection, cross-site scripting (XSS), remote file inclusion, and distributed denial-of-service (DDoS) attacks. The results from extensive testing and real-world deployment scenarios have validated the system's high detection accuracy, low false positive rates, and its ability to generalize well across unknown or zero-day attack patterns. The integration of a robust data preprocessing pipeline, effective feature extraction, and a continuous learning feedback loop ensures that the WAF remains updated and capable of adapting to new threat vectors without requiring constant human intervention. Furthermore, the system's real-time response capability and minimal processing latency make it suitable for high-traffic environments, ensuring seamless protection without compromising performance. The intelligent logging, alerting, and behavioral analysis components add further depth by enhancing visibility and aiding administrative decision-making. Overall, this intelligent WAF framework not only enhances the security posture of web applications but also introduces a scalable, efficient, and future-ready solution for organizations aiming to defend their digital assets against an increasingly sophisticated and dynamic threat landscape.

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