



Intelligent Web Application firewall

A senior project submitted in partial fulfillment of requirements for the degree of Bachelor of Computer and Artificial Intelligence

“Information Security and Network” programs

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Table of contents

1.Introduction	6
1.1. The Digital Age and the Rising Threat to Web Applications	6
1.2. The Emergence of a Specialized Defense: Defining the Web Application Firewall (WAF)	7
1.3. The Evolution of WAFs: A Legacy of Adaptation in a Cybersecurity Arms Race.....	8
1.3.1. First Generation: The Era of Signatures (Early 2000s).....	8
1.3.2. Second and Third Generations: The Growth of Intelligence (Mid- 2000s - Late 2010s)	8
1.4. The Problem Statement: The Limits of Traditional and Signature- Based WAFs	9
1.5. The Proposed Solution: A Synergistic, AI-Driven Security Paradigm.....	10
1.6. Aims and Objectives of the Project.....	11
1.7 The Limitations of WAFs.....	11
1.7.1. The Early Days: The Emergence of Application-Layer Threats (Late 1990s - Early 2000s)	12
1.7.2. First Generation WAFs: The Era of Rule-Based and Signature Matching (Early 2000s)	13
1.7.3. Second Generation WAFs: The Dawn of Anomaly Detection and Hybrid Models (Mid-2000s - Mid-2010s)	15
1.7.4. Third Generation WAFs: The Age of Behavioral Analysis and Global Intelligence (Mid-2010s - Late 2010s)	17
1.7.5 Current Generation WAFs: The AI and Cloud Revolution (Late 2010s - Present).....	18
Chapter 2: Literature Review and Theoretical Foundations.....	21
2.1 Web Application Security: An Overview	21
2.2 Common Web Application Attacks	22
2.3 Web Application Firewalls (WAFs): Types and Capabilities	24
Core Functions of a WAF	24
Types of WAF Deployments	24
2.4 Artificial Intelligence in Cybersecurity	27
2.4.1AI Applications in Cybersecurity	27
2.4.2 Core AI Techniques Used in Cybersecurity	28

2.4.3 Role of AI in Web Application Firewalls	28
2.4.4 Implementation in Our Project	29
Conclusion	29
2.5 Review of Existing WAF Solutions and Research Gaps	30
2.5.1 Overview of Existing WAF Solutions.....	30
Limitations of Existing Solutions.....	30
Identified Research Gaps	31
Contribution of This Project	31
Why Traditional Firewalls Are Not Enough for Web Applications ?	32
Chapter 3: System Architecture and Design.....	33
3.1 Proposed System Overview	34
3.2 High-Level Architectural Design	35
3.3 Use Case Modeling.....	36
3.4 Context Diagram	39
3.5 Data Flow Diagram (DFD)	42
3.6 Sequence Diagram	45
3.7 Class Diagram	47
3.8 System Block Diagram.....	50
3.9 Activity Diagram	54
Chapter 4: System Implementation and Training	57
4.1 Development Environment and Tools.....	58
4.1.1 Programming Language: Python	58
4.1.2 Core Libraries and Frameworks.....	59
4.1.3 Integrated Development Environment (IDE).....	59
4.1.4 Hardware and Operating System Setup.....	60
4.1.5 Environment Configuration and Version Control	60
4.2 Dataset Preparation and Labeling.....	60
4.2.1 Data Collection and Sources	61
4.2.2 Feature Selection and Representation	61
4.2.3 Data Cleaning and Normalization.....	62
4.2.4 Labeling Strategy.....	62
4.2.5 Dataset Structure and Storage	63

4.3 AI Model Training	63
4.3.1 Model Selection	64
4.3.2 Training Process	64
4.3.3 Model Evaluation and Metrics	65
4.4 WAF Backend Implementation	66
4.4.1 Flask Web Framework	67
4.4.2 Key Functional Modules	67
4.4.3 API Endpoints.....	69
4.4.4 Request Inspection Workflow	69
4.4.5 Example Request Handling	70
4.4.6 Deployment and Testing	71
4.5 Telegram Bot Integration.....	71
4.5.1 Purpose of Telegram Integration.....	71
4.5.2 Telegram Bot Setup	72
4.5.3 Bot Functionality and Features	72
4.5.4 Implementation in Python.....	73
4.5.5 Advantages of Telegram for Security Alerting.....	74
4.5.6 Testing and Verification	74
4.6 Rule-Based Detection Module.....	74
4.6.1 Purpose of the Rule-Based Module.....	75
4.6.2 Rule Format and Storage	75
4.6.3 Types of Attacks Detected.....	76
4.6.4 Rule Engine Implementation	76
4.6.5 Integration with WAF Decision Logic.....	77
4.6.6 Updating and Extending Rules	77
4.6.7 Benefits and Limitations	78
Chapter 5: Testing, Results, and Evaluation	78
5.1 Testing Methodology and Scenarios	79
5.1.1 Test Environment Setup.....	79
5.1.2 Test Scenarios	80
5.1.3 Evaluation Focus	82
5.2 Experimental Results and Evaluation Metrics	82

5.2.1 Performance Evaluation	83
5.2.2 System Latency and Performance	84
5.2.3 Alerting and Notification System	84
5.2.4 Log Integrity and Logging System.....	85
5.2.5 Usability Testing	86
5.2.6 Summary of Experimental Results	87
5.3 Limitations and Future Work.....	88
5.3.1 Limitations of the Current System.....	88
2. False Positives and False Negatives.....	89
5.3.2 Future Work and Enhancements.....	91
5.4 User Control from our IWAF	93
5.5 Conclusion	93
Chapter 6: System Implementation and Deployment	95
6.2.1 Installing the WAF Software.....	97
6.2.2 Configuring the WAF	98
Conclusion	99

1.Introduction

1.1. The Digital Age and the Rising Threat to Web Applications

In today's world, nearly every aspect of life relies on the internet. From online shopping and digital banking to remote learning and instant messaging, web applications have become the core platform for both individuals and organizations. Government agencies, banks, healthcare systems, and businesses all depend heavily on these applications for secure operations and communication.

However, this digital transformation has shifted the focus of cyber attackers. Where traditional threats once targeted infrastructure and network services, modern attackers now focus on the **application layer (Layer 7)**. This is where sensitive user actions occur — logins, data transfers, form submissions — and it is increasingly difficult to defend using legacy security systems.

Traditional tools like firewalls and Intrusion Prevention Systems (IPS) are no longer enough. These systems operate at lower layers of the OSI model and cannot inspect or understand the complexities of HTTP traffic. Application-layer attacks often look like regular user activity, making them difficult to detect and stop without application-aware security.

To address this growing challenge, our project presents an **Intelligent Web Application Firewall (WAF) based on Artificial Intelligence (AI)**. Unlike traditional WAFs, our intelligent WAF uses **machine learning models trained on historical attack data** to detect suspicious behavior and unknown (zero-day) threats in real-time. By learning what normal traffic looks like and identifying deviations, the AI-based WAF can block sophisticated attacks such as SQL injection, XSS, CSRF, and more.

Additionally, we implemented a **Telegram Bot integration** that instantly **notifies the WAF administrator** if an attack is detected. This ensures that response times are minimized and administrators can take immediate action to investigate and mitigate threats.

Our solution demonstrates how modern AI technology can be applied to enhance application security, reduce false positives, and automate threat detection – all while providing a responsive communication channel for real-time alerts.

1.2. The Emergence of a Specialized Defense: Defining the Web Application Firewall (WAF)

In response to this critical security gap, a specialized technology emerged: the **Web Application Firewall (WAF)**. A WAF is a dedicated security solution meticulously engineered to protect web applications from a vast array of sophisticated, application-layer attacks by filtering, monitoring, and blocking malicious HTTP and HTTPS traffic.

Its fundamental distinction lies in its operational domain within the OSI model. Unlike a traditional network firewall, which is a network generalist operating at the Network and Transport layers (Layers 3 and 4), the WAF is a **Layer 7 specialist**. This position affords it a deep, contextual understanding of the application's native language—HTTP/S. A WAF can deconstruct and analyze the entire conversation between the client and the application, including:

- **HTTP Methods** (e.g., GET, POST, PUT) to ensure they are used legitimately.
- **HTTP Headers** to detect anomalies in elements like User-Agent or Cookie values.
- **URL Query Strings and Parameters**, which are primary vectors for injection attacks.
- **Request Body Payloads**, including multipart form data, JSON, and XML, to inspect for embedded scripts, malicious commands, or malformed data structures.

This granular visibility is precisely what empowers a WAF to identify and neutralize threats that are completely invisible to lower-layer security devices.

Functionally, a WAF typically operates as a **reverse proxy**, an architectural model of great significance. It positions itself in front of the web servers, intercepting all client requests. It then inspects these requests against a security policy, and only forwards legitimate, sanitized traffic to the application server. This architecture provides critical benefits, such as decoupling security from the application code, enabling centralized policy enforcement, and hiding the true IP addresses of the backend servers.

1.3. The Evolution of WAFs: A Legacy of Adaptation in a Cybersecurity Arms Race

The history of the WAF is a compelling narrative of continuous adaptation. Tracing this evolution is crucial to understanding the limitations of past approaches and the necessity of the AI-driven paradigm proposed in this project.

1.3.1. First Generation: The Era of Signatures (Early 2000s)

The first WAFs emerged as a direct response to the rise of dynamic, database-driven applications and the concurrent discovery of foundational vulnerabilities like SQL Injection (SQLi) and Cross-Site Scripting (XSS).

- **Operating Model:** These systems were almost exclusively based on a **negative security model** (blacklisting). They used manually configured rules and databases of "signatures"—predefined patterns representing known attacks. A request was blocked if it matched a known bad pattern, such as containing the string 'UNION SELECT'.
- **Pivotal Technologies:** The open-source **ModSecurity** engine became a cornerstone of this era, providing a flexible rule engine that powered many commercial and custom WAF solutions. The **OWASP ModSecurity Core Rule Set (CRS)** emerged as a vital, community-driven project to provide a baseline set of generic attack detection rules.
- **Inherent Flaws:** This signature-based approach was inherently reactive. Attackers quickly learned to bypass these systems using simple evasion techniques like character encoding, case alteration, or inserting null bytes, which naive regular expression-based signatures would fail to catch. The maintenance overhead was enormous, and the rate of false positives was high.

1.3.2. Second and Third Generations: The Growth of Intelligence (Mid-2000s - Late 2010s)

Driven by increasing attack sophistication and regulatory pressures like PCI DSS, WAFs were forced to become more intelligent.

- **Anomaly Detection:** The second generation introduced **anomaly detection**. These WAFs would establish a statistical baseline of "normal" traffic and flag significant deviations, providing a first line of defense against unknown threats. They also became **stateful**, tracking user sessions to detect multi-step attacks like brute-forcing.

- **Behavioral Analysis and Threat Intelligence:** The third generation took this a step further with true **behavioral analysis**. By profiling user and bot behavior (e.g., analyzing mouse movements, page sequencing), these systems could more accurately differentiate humans from advanced automated threats. This era also saw the crucial integration of **global threat intelligence feeds** to proactively block known malicious actors and the development of dedicated **API security** capabilities to protect the new backbone of modern applications.

1.4. The Problem Statement: The Limits of Traditional and Signature-Based WAFs

Despite this evolution, even the most advanced non-AI WAFs that rely on signatures and basic heuristics have reached a critical ceiling. They are struggling to contend with the current threat landscape, creating a compelling need for the solution proposed in this project. The core problems are:

- **The Zero-Day Vulnerability Crisis:** Traditional WAFs are fundamentally incapable of defending against zero-day exploits. By the time a signature is developed and deployed by a vendor, threat actors have often had a significant window of opportunity to cause widespread damage.
- **The False Positive/Negative Dilemma:** There is a constant, painful trade-off. If security rules are too strict, the WAF generates a high number of **false positives**, blocking legitimate users and disrupting business. If the rules are too loose, the WAF suffers from **false negatives**, allowing real attacks to pass through undetected. This dilemma makes effective management a nearly impossible balancing act.
- **Inability to Understand Context and Intent:** A signature-based WAF lacks true contextual understanding. It cannot discern intent. It might see a request containing the word SELECT and block it, failing to understand if it's part of an SQL injection attack or simply a user posting a question about SQL on a programming forum.
- **Failure Against Sophisticated Automation:** Modern botnets use thousands of distributed IPs, rotate their browser fingerprints, and mimic human behavior to conduct "low-and-slow" attacks that fly under the radar of simple rate-limiting and signature-based detection.

1.5. The Proposed Solution: A Synergistic, AI-Driven Security Paradigm

This project addresses these fundamental limitations by architecting a next-generation, AI-powered WAF that represents a paradigm shift from reactive filtering to proactive, intelligent defense. Our solution is built on a synergistic, multi-layered defense strategy:

1. **AI-Driven Threat Detection:** The core of our solution is a sophisticated Machine Learning engine. Instead of relying on static signatures, it learns the unique behavioral "fingerprint" of the application it protects. By establishing a high-fidelity baseline of normal activity, it can detect any anomalous deviation in real-time. This allows it to identify not only known attack patterns but also heavily obfuscated payloads and, most critically, **previously unseen zero-day exploits** based on their anomalous characteristics alone.
2. **Hybrid Threat Intelligence via VirusTotal Integration:** We recognize that no single system has a complete view of the threat landscape. Our WAF enriches its decision-making by integrating with the **VirusTotal API**. When encountering a suspicious file upload or URL, it can query VirusTotal to leverage the collective intelligence of over 70 security vendors. A high-risk score from VirusTotal provides a powerful, external confirmation, dramatically increasing detection confidence and reducing false positives.
3. **High-Velocity Incident Response via Telegram Bot:** Detection is only half the battle. When our WAF identifies and blocks a critical threat, it doesn't just silently log the event. It instantly triggers a notification through a dedicated **Telegram Bot**. This pushes a real-time, detailed alert—including the attack type, source IP, targeted URL, and the malicious payload—directly to the security administrator's designated device. This transforms the WAF from a passive defense tool into an active participant in the incident response lifecycle, drastically reducing the mean time to respond (MTTR).
4. **Customizable Rule Sets:** While AI is the core, we understand the need for granular control. Our system allows administrators to implement custom rule sets that work in concert with the AI engine, enabling them to tailor security policies to their specific application needs and compliance requirements.

1.6. Aims and Objectives of the Project

The core aim of this project is to engineer and validate a robust, proof-of-concept intelligent WAF that demonstrates the superiority of a multi-layered, AI-driven security architecture. The specific objectives are:

- **To design** a scalable, modular WAF architecture that seamlessly integrates static analysis, ML inference, external API calls, and a real-time notification system.
- **To implement** a high-performance data processing pipeline capable of extracting meaningful features from raw HTTP/S traffic in real-time.
- **To develop, train, and validate** a suite of machine learning models optimized for high-accuracy detection of web attacks with an exceptionally low false-positive rate.
- **To build and integrate** the functional modules for interacting with the VirusTotal API and the Telegram Bot API.
- **To rigorously evaluate** the complete system's performance against a comprehensive set of metrics, including detection accuracy against obfuscated and zero-day attack simulations.

1.7 The Limitations of WAFs

The emergence and evolution of the Web Application Firewall were not an academic exercise; they were a direct and necessary response to a profound paradigm shift in the landscape of cybersecurity. The history of WAFs is a compelling narrative of a continuous technological arms race between defenders and adversaries, where each generation of protection was born from the failure of the last to withstand a new class of threats. To fully appreciate the necessity of the AI-driven approach proposed in this project, it is essential to trace this evolutionary journey.

Initially, in the nascent days of the internet, security concerns were primarily focused on the network perimeter. The primary goal was to protect the underlying infrastructure—servers, routers, and switches—from direct intrusion, network scans, or volumetric denial-of-service attacks. Consequently, the first wave of security devices, such as traditional network firewalls and Intrusion Detection Systems (IDS), were developed to address these threats. These tools operate at the lower layers of the network stack (Layers 3 and 4 of the OSI model), making decisions based on network addresses, ports, and protocols.

However, as the internet transformed from a simple information delivery mechanism into a dynamic platform hosting complex, interactive web applications, a new and far more insidious class of vulnerabilities emerged. These vulnerabilities resided not in the network infrastructure itself, but deep within the application's logic, its code, and

its methods of handling user-supplied data. These application-layer threats demanded a new, specialized defense mechanism—one capable of understanding the nuanced grammar of Hypertext Transfer Protocol (HTTP) and decrypting HTTPS traffic to inspect its content. This necessity gave rise to the Web Application Firewall (WAF), a technology designed with the specific purpose of protecting web applications from attacks targeting Layer 7. Tracing the history of WAFs reveals this continuous adaptation to an ever-changing threat landscape, a journey driven by escalating attack sophistication, the rapid evolution of web technologies, and the exponentially growing value of the data processed by web applications.

1.7.1. The Early Days: The Emergence of Application-Layer Threats (Late 1990s - Early 2000s)

In the late 1990s and early 2000s, web development underwent a revolution. The web transitioned from static HTML pages to interactive, database-driven experiences powered by server-side scripting languages like **ASP (Active Server Pages)**, **JSP (JavaServer Pages)**, and **PHP (Hypertext Preprocessor)**, with backend databases like **MySQL** and **Microsoft SQL Server** serving as data repositories. This dynamism, which enabled everything from e-commerce shopping carts to online forums, also inadvertently introduced new and dangerous avenues for attack. Developers could now dynamically construct HTML pages and SQL queries based on user-supplied data—a powerful feature that, if not implemented with stringent security controls, created a direct conduit for attackers to inject malicious content.

Attackers quickly discovered that by craftily manipulating the data submitted in user input fields, they could inject malicious code or database commands that the backend application would then process as if they were legitimate instructions. This led to the rise of several prominent early application-layer vulnerabilities:

- **SQL Injection (SQLi):** This devastating attack exploited flaws in how applications constructed SQL queries from user input. For instance, a vulnerable login query might look like: `SELECT * FROM users WHERE username = ' + userInput + ';`. An attacker could provide an input like `' OR '1'='1' --` which would transform the query into `SELECT * FROM users WHERE username = ' OR '1'='1' --';`. Since `'1'='1'` is always true, this manipulated query could bypass authentication entirely. A successful SQLi could lead to complete data theft, modification, deletion, or even full administrative control over the database server via command execution.
- **Cross-Site Scripting (XSS):** This attack involved injecting malicious client-side scripts (typically JavaScript) into web pages that would later be viewed by other users. This allowed the attacker's script to execute within the security context of the victim's browser, enabling them to steal session cookies, hijack user accounts, deface websites, or redirect users to phishing sites.

- **Command Injection:** This class of vulnerability exploited flaws in applications that called system commands. By injecting shell metacharacters (e.g., ;, &&, |), an attacker could execute arbitrary operating system commands on the web server itself, leading to a full system compromise.
- **Directory Traversal (or Path Traversal):** This attack allowed access to files and directories outside of the intended web root directory. By manipulating file path variables with ../ sequences, attackers could read sensitive files like /etc/passwd or application configuration files containing database credentials.

Traditional network firewalls were anatomically blind to these attacks. To a Layer 3/4 firewall, an HTTP packet carrying a legitimate user comment and one carrying a malicious XSS payload are indistinguishable. Both are simply valid TCP segments destined for an allowed port (e.g., 80 or 443). This created a significant and dangerous security gap, leaving the most valuable part of the digital infrastructure—the application—completely exposed. It became painfully clear that a new defense mechanism was needed, one that could understand the HTTP protocol fluently and analyze the application-specific content within web traffic.

1.7.2. First Generation WAFs: The Era of Rule-Based and Signature Matching (Early 2000s)

The first generation of Web Application Firewalls emerged as a direct response to these escalating application-layer threats. These early WAFs were foundational but simplistic, primarily based on deterministic rule-based logic and signature matching.

- **Rule-Based Systems:** At their core, these WAFs operated by applying a set of predefined rules, often in the form of regular expressions (regex), to incoming HTTP requests and outgoing responses. These rules were often configured manually by security administrators to block requests containing specific keywords or patterns associated with attacks. For example:
 - Blocking requests where a parameter contains SQL keywords like 'UNION SELECT' or comment characters like '--'.
 - Blocking requests containing common HTML/JavaScript tags used in XSS, such as '<script>' or event handlers like 'onload='.
 - Enforcing input validation by limiting the length of input fields to prevent buffer overflows.
 - Blocking direct requests to administrative URLs or sensitive configuration files.
- **Signature Matching:** Alongside simple rules, WAFs incorporated databases of "signatures," which were predefined patterns representing known attack

vectors. This was directly analogous to how early anti-virus software detected malware. When an incoming request matched a signature, the WAF would block it. These signatures were typically derived from analyzing known exploits for common vulnerabilities in popular web platforms like WordPress or frameworks like Struts.

- **Positive vs. Negative Security Models:** Early WAFs almost exclusively relied on a "**negative security model**" (also known as a blacklist). This approach involves defining what is *bad* and blocking any traffic that matches those definitions. While relatively straightforward to implement and manage, this model is inherently reactive. It is fundamentally incapable of protecting against new, unknown attacks (zero-day threats) for which no signature exists. Some early WAFs also introduced the concept of a "**positive security model**" (a whitelist), which takes the opposite approach: it defines what is *good* or legitimate traffic and blocks everything else. While offering theoretically stronger protection against unknown threats, positive security models proved to be extremely complex to configure and maintain. They required a deep, exhaustive understanding of every part of the application's expected behavior and had to be constantly updated as the application changed, making them brittle and impractical for dynamic applications.
- **Deployment:** The first generation of WAFs were typically deployed as on-premises **hardware appliances** positioned in front of web servers, acting as reverse proxies. This required significant upfront capital expenditure (CAPEX), network architecture changes, and dedicated data center space.
- **Severe Limitations:** Despite providing a crucial new layer of defense, these early WAFs had significant limitations that defined the next stage of evolution:
 - **High Maintenance Overhead:** Relying heavily on manual rule creation and signature updates was a labor-intensive and reactive process, requiring a dedicated team of security analysts.
 - **Pervasive False Positives/Negatives:** Simple pattern matching was a blunt instrument. It often led to **false positives** (blocking legitimate traffic that accidentally contained a suspicious keyword) or **false negatives** (failing to block malicious traffic that used slight variations or encoding to bypass the signature).
 - **Critical Lack of Context:** These WAFs were typically **stateless**. They analyzed each HTTP request in complete isolation, lacking the ability to understand the state of a user session or correlate multiple seemingly innocuous requests into a recognized attack sequence.

- **Performance Overhead:** Deep packet inspection, especially the decryption and re-encryption of SSL/TLS traffic, added significant latency to web requests.

An important open-source project that emerged during this period and significantly contributed to WAF development is **ModSecurity**. Originally created by Ivan Ristić in 2002, ModSecurity started as an Apache module but later expanded to support other web servers like Nginx and IIS. It provided a flexible engine for analyzing HTTP traffic and a rich rule language, becoming a cornerstone for many open-source and commercial WAF solutions. The associated **OWASP ModSecurity Core Rule Set (CRS)** became a widely adopted, community-vetted collection of generic attack detection rules, helping to provide a baseline level of protection against many common threats and democratizing access to WAF technology

1.7.3. Second Generation WAFs: The Dawn of Anomaly Detection and Hybrid Models (Mid-2000s - Mid-2010s)

The second generation of WAFs represented a significant leap forward, designed specifically to overcome the inherent limitations of pure signature matching by incorporating more dynamic, intelligent analysis techniques.

- **The Paradigm Shift to Anomaly Detection:** The most important innovation of this era was the practical implementation of **anomaly detection**. Instead of relying solely on a list of known "bad" patterns, these WAFs would enter a "learning mode" to build a baseline profile of what constituted "normal" traffic for a specific application. This baseline could include metrics like typical request rates, average and maximum parameter lengths, common character sets, URL access patterns, and session durations. Any subsequent traffic that significantly deviated from this learned baseline could be flagged as suspicious. This was a revolutionary step, as it provided, for the first time, a viable layer of defense against novel, mutated, and zero-day attacks for which no signature existed. Anomaly detection complemented signature matching, providing a more robust, layered defense.
- **Improved Rule Engines and Hybrid Models:** WAFs developed more sophisticated rule engines and began to employ **risk-based scoring**. Instead of a binary block/allow decision, a request would accumulate a "risk score" based on multiple indicators. For example, a request from a suspicious IP address might get 10 points, a request with an unusual User-Agent might get 5 points, and a request containing a suspicious keyword might get 20 points. Only if the total score crossed a

predefined threshold would the request be blocked. This nuanced approach significantly reduced false positives. The **hybrid security model** became standard, leveraging the efficiency of signatures for known threats while using anomaly detection and risk scoring to catch more advanced attacks.

- **Stateful Inspection and Session Tracking:** These WAFs gained the ability to be **stateful**, meaning they could track and understand the sequence of requests within a single user session. This was a critical advancement. A stateless, first-generation WAF would see ten individual, seemingly harmless login attempts from ten different IPs as separate events. A stateful WAF could correlate these events, recognize them as a distributed brute-force attack, and take action. This ability to understand session context was vital for detecting multi-step attacks and for more accurately distinguishing legitimate user behavior from malicious automated traffic.
- **Integration with Vulnerability Management and "Virtual Patching":** A powerful synergy emerged as WAFs began to integrate with web application vulnerability scanners (Dynamic Application Security Testing - DAST tools). When a scanner discovered a specific vulnerability (e.g., an XSS flaw on a specific page), its findings could be automatically exported and translated into a precise WAF rule. This created the capability of "**virtual patching**." The WAF could immediately block any attempt to exploit the discovered vulnerability, providing instant protection and buying the development team crucial time to develop and deploy a permanent code-level fix without leaving the application exposed.
- **Better Management and Usability:** Recognizing the complexity of WAF management, vendors invested heavily in creating more user-friendly graphical interfaces, detailed reporting and visualization capabilities, and tools designed to help administrators tune rules and investigate alerts more efficiently.

While hardware appliances remained prevalent, this era also saw the first **early cloud deployments**, with some vendors starting to offer WAF capabilities as a managed service, foreshadowing the major shift to come. This generation, with its focus on anomaly detection, stateful inspection, and virtual patching, marked a significant step forward, making WAFs far more effective and harder to bypass. However, the statistical anomaly detection models still required significant manual tuning, and sophisticated attackers could still find ways to craft malicious traffic that blended in with legitimate patterns, setting the stage for the next evolution.

1.7.4. Third Generation WAFs: The Age of Behavioral Analysis and Global Intelligence (Mid-2010s - Late 2010s)

As attacks became more targeted, stealthy, and reliant on sophisticated botnets, WAF technology needed to become even more dynamic and context-aware. The third generation evolved beyond simple statistical anomalies to focus on holistic behavioral analysis and the power of collective, global intelligence.

- **Advanced Behavioral Analysis:** This capability went far beyond simple anomaly detection. It involved building detailed profiles not just of application traffic, but of **user and bot behavior**. By leveraging techniques like client-side JavaScript interrogation, the WAF could analyze sequences of actions, time spent on pages, mouse movements, typing cadence, and browser/device fingerprinting. This rich behavioral data allowed WAFs to differentiate between legitimate human users, sophisticated (but "headless") bots, and automated attack tools with incredibly high accuracy. This was particularly effective against threats like Advanced Persistent Bots (APBs), application-layer DDoS attacks, and credential stuffing campaigns.
- **Threat Intelligence Integration:** WAFs began to integrate with **global threat intelligence feeds** in real-time. These feeds, curated by security research teams around the world, provided up-to-the-second information about known malicious IP addresses, newly discovered botnet command-and-control (C&C) servers, attacker signatures from emerging campaigns, and malicious TOR exit nodes. By leveraging this collective intelligence, a WAF could proactively block traffic from known bad sources before an attack was even launched or apply stricter inspection rules to traffic originating from suspicious geolocations or networks.
- **Dedicated Advanced Bot Management:** Bot management evolved from a simple feature into a core WAF capability. This involved advanced techniques for identifying and classifying different types of bots: "**good bots**" like search engine crawlers (Googlebot, Bingbot), which are essential for business, and "**bad bots**" like content scrapers, spammers, credential stuffers, and vulnerability scanners. The WAF could then apply different actions: allowing good bots, blocking known bad bots, and **challenging** suspicious or unknown bots with methods like CAPTCHAs, cryptographic proofs-of-work, or advanced JavaScript tests to verify they were being run by a real human in a standard browser.

- **Comprehensive API Security:** With the explosion of mobile applications and single-page applications (SPAs), APIs became the de facto backbone of the modern web. The third generation of WAFs developed specialized capabilities for **API security**. This went beyond just inspecting JSON or XML. It involved the ability to ingest API specifications like **OpenAPI (formerly Swagger) schemas**. By understanding the API's documented structure, the WAF could enforce a positive security model, automatically validating that every API request conformed to the expected methods, endpoints, parameters, and data types, thus protecting against a wide range of API-specific attacks like parameter manipulation or broken object-level authorization (BOLA).
- **Mainstream Adoption of Cloud-Based Deployment:** In this era, **cloud-based WAFs** became mainstream and, for many, the preferred deployment model. Major cloud providers like **AWS (AWS WAF)**, **Microsoft (Azure WAF)**, and **Google (Cloud Armor)** offered tightly integrated WAF services. Specialized security vendors like **Cloudflare**, **Akamai**, and **Imperva** redefined the market by offering WAF protection as a scalable, easy-to-deploy service delivered from a global network edge. This model offered customers pay-as-you-go pricing, automatic scaling, and massive DDoS absorption capacity, significantly lowering the barrier to entry for robust WAF protection and aligning perfectly with the shift to cloud-native application architectures.

1.7.5 Current Generation WAFs: The AI and Cloud Revolution (Late 2010s - Present)

The current generation of WAFs, which is the generation our project belongs to, is a huge step forward. It's defined by two main ideas: making WAFs much smarter using **Artificial Intelligence (AI)** and **Machine Learning (ML)**, and making them part of bigger, more connected security platforms, usually in the cloud.

AI and Machine Learning Integration: Making the WAF "Smart"

Think of older WAFs as security guards with a book of photos of known criminals. They can only catch someone if their face is in the book. But what if a new criminal comes along? The guard won't recognize them. Machine Learning gives the security guard a brain. Instead of just a photo book, the guard now learns the normal daily routine of everyone in the building. They

know who arrives at what time, where they go, and what they do. The ML-powered guard can now catch a criminal not because they've seen their face before, but because the criminal is doing something that is not "normal."

This is how ML algorithms are used in modern WAFs, and it's the core of our project:

- **Improve Anomaly Detection:** Older WAFs could do basic anomaly detection, like flagging someone wearing a winter coat in the summer. But it would lead to many false alarms. ML models are much smarter. They learn the complex patterns of what is normal for your specific application. They can understand the context. For example, they learn that a lot of login attempts from one person is normal, but a lot of login attempts for *different* people from one computer is a sign of a credential stuffing attack. This intelligence greatly reduces false alarms and helps it find very subtle attacks that older systems would miss.
- **Identify Novel Attacks (Zero-Days):** A "zero-day" attack is a brand-new attack that hackers just invented. No one has a signature or rule for it yet. This is where ML is most powerful. Since the ML model knows what "normal" behavior looks like, it can easily spot an attack it has never seen before, simply because the attack's behavior is weird and doesn't fit the normal pattern. It doesn't need a photo of the criminal; it just needs to recognize that the person's actions are suspicious.
- **Automate Policy Updates:** In the past, a human security expert had to manually write new security rules all the time. This is slow and expensive. ML helps automate this. An ML system can analyze the new attacks it blocks and learn from them. It can then automatically suggest new, smarter rules or even adjust its own understanding to get better at blocking future attacks. It's like a security guard who learns and gets smarter on their own after every incident.
- **Enhance Bot Detection:** It's very hard to tell the difference between a real human user and a sophisticated "bot" (a computer program trying to act like a human). For example, bots are used to buy up all the tickets to a concert in seconds. An ML model can detect these bots. It can analyze things like how the "user" moves the mouse, the timing between clicks (a human is never perfectly regular, a bot often is), and other small behaviors to accurately decide if it's a real person or a program.
- **Analyze Attack Campaigns:** Imagine a hacker is trying to attack 100 different websites at the same time from 100 different computers. To each individual website, it might look like one small, random attack.

But a smart AI system can see the bigger picture. It can collect the information from all 100 websites, connect the dots, and realize it's one big, coordinated attack campaign from a single group. This helps security teams understand the true threat they are facing.

In simple terms, ML in WAFs represents a shift from a fixed, "dumb" set of rules to a flexible, "smart" brain that can learn and adapt. While we still use simple rules to block simple, known attacks (because it's fast), ML gives us the crucial power to detect advanced attacks that don't follow any known pattern.

Other Features of the Current Generation:

- **Integration into Cloud Security Platforms:** Instead of buying a physical WAF box, WAF functionality is now often part of a bigger service. Think of it like a smartphone. In the past, you had a phone, a separate camera, and a separate music player. Now, the camera and music player are just apps (features) on your phone. Similarly, a WAF is now often a feature within a **Content Delivery Network (CDN)** or a cloud provider's security services. This makes it easier to set up, manage, and scale.
- **Advanced API Protection:** Modern apps use APIs to talk to each other. Modern WAFs have special features to protect these APIs, like reading the API's documentation (its OpenAPI schema) to automatically know what a normal API request should look like.
- **Improved Performance and Scalability:** Cloud-based WAFs use the massive power of the cloud to handle huge amounts of traffic. They can easily stop huge DDoS attacks that would crush a single hardware WAF.
- **Focus on User Experience:** Modern WAFs try hard not to bother legitimate users. They use techniques like risk scoring. For example, instead of blocking a slightly suspicious user immediately, they might just show them a CAPTCHA ("Prove you're human") to verify them without kicking them out. This is called an "adaptive challenge."

The integration of AI/ML is the key thing that makes this generation of WAFs different and so much more powerful. It allows them to be more adaptive, more accurate, and more autonomous. However, it's not magic. It has challenges, like needing a lot of good data to learn from, and the fact that smart hackers are now trying to invent ways to fool the AI itself. **Our project focuses on building such an intelligent WAF while being mindful of these challenges.**

Chapter 2: Literature Review and Theoretical Foundations

2.1 Web Application Security: An Overview

Web applications are now a big part of our everyday life. People use them to shop online, pay bills, access government services, book appointments, and manage their personal or business information. Companies also use web applications to provide services to users all over the world. Because of this, web applications often deal with sensitive data like usernames, passwords, ID numbers, credit card details, and other private information.

Since these applications are connected to the internet, they are open to everyone—including hackers. This makes them an easy target for cyberattacks. Many attackers try to find weaknesses in the application's code or in the way it processes user data. These weaknesses are called **vulnerabilities**. If attackers can find a way to use these vulnerabilities, they can steal data, damage systems, or take control of the application.

Web application security is the process of protecting these applications from such attacks. It includes writing secure code, checking for common problems, and using tools like **Web Application Firewalls (WAFs)** to block dangerous requests. One big challenge is that most of the attacks happen at the **application layer (Layer 7)**, which is where users interact with the app. Traditional firewalls only protect lower layers, like the network, and cannot detect many of these advanced attacks.

Some of the most common attacks on web applications include:

- **SQL Injection** – when attackers send harmful commands to the database.
- **Cross-Site Scripting (XSS)** – when attackers add malicious scripts to web pages.
- **Cross-Site Request Forgery (CSRF)** – when attackers trick users into doing things without knowing.

To help developers and security teams, the **OWASP Top Ten** project lists the most dangerous web application vulnerabilities. This list is used by professionals around the world to improve their security practices.

Today's web applications use many new technologies like JavaScript, APIs, and third-party tools. These tools help improve user experience, but they also create more security risks. Attackers are getting smarter and often use automated tools or fake traffic (bots) to bypass basic security systems.

Because of this, we need better solutions that can detect new and advanced attacks. That's why our project uses **Artificial Intelligence (AI)** to improve the Web Application Firewall. Instead of only using fixed rules, our **Intelligent WAF** can learn from past traffic and detect strange behavior that might be an attack. We also added a **Telegram bot** to send real-time alerts to the admin if an attack happens.

In short, **web application security is very important** in today's digital world. Without it, private data, company systems, and user trust can be easily lost. Our project helps solve this problem by using AI to make web security smarter, faster, and more accurate.

2.2 Common Web Application Attacks

Web applications often deal with user input—like login forms, search bars, contact forms, and payment pages. If this input is not properly checked or cleaned, it can lead to serious security problems. Hackers take advantage of these weak spots to send harmful data, steal information, or even take control of the system.

Below are some of the **most common attacks** that target web applications:

1-SQL Injection (SQLi)

Hackers send special input to a website form that tricks the database into running unwanted commands.

It can allow attackers to steal, change, or delete data from the database.

2-Cross-Site Scripting (XSS)

This attack involves injecting harmful scripts (like JavaScript) into a web page that other users will view.

These scripts can steal user cookies, redirect users, or perform actions on their behalf.

3-Cross-Site Request Forgery (CSRF)

In a CSRF attack, the hacker tricks a logged-in user into making a request they didn't mean to make.

This can result in actions like changing account details or transferring money.

4- Command Injection

The attacker adds dangerous operating system commands through input fields.

This can lead to full server access or letting the attacker run harmful programs.

5-Directory Traversal

By manipulating file paths in URLs, attackers try to access sensitive system files outside the web app folder.

This can expose passwords, system settings, or other protected data.

6-Broken Authentication

Hackers take advantage of poor login systems or session handling.

They might log in as other users or even as an admin without needing the correct password.

7-Security Misconfiguration

Web apps or servers may be incorrectly set up (e.g., default passwords or unnecessary access permissions).

Attackers use these misconfigurations to gain unauthorized access.

8-Sensitive Data Exposure

Some applications don't encrypt or properly protect sensitive information like passwords or payment details.

If a hacker gets access, they can steal valuable personal or business data.

These attacks are dangerous because they can happen without the user noticing anything wrong.

That's why tools like **WAFs (Web Application Firewalls)** and **AI-based detection systems** are needed—to inspect traffic deeply and stop suspicious actions before they harm the system.

2.3 Web Application Firewalls (WAFs): Types and Capabilities

As web applications have become more complex and widely used, attackers have shifted their focus to the **application layer (Layer 7)** of the OSI model. Traditional network security tools, like firewalls and intrusion prevention systems (IPS), work mainly at the network and transport layers. While they are good at stopping low-level attacks (like port scanning or blocking IP addresses), they cannot inspect or understand the structure and behavior of web traffic—such as login forms, search queries, or file uploads.

This gap in security has created the need for a specialized tool that can understand how web applications work and detect harmful behavior inside HTTP and HTTPS requests. This tool is called a **Web Application Firewall (WAF)**.

A **Web Application Firewall** acts as a filter between the user and the web application. It monitors all requests coming from users (or bots) and decides whether to allow, block, or flag them based on a set of security rules. WAFs can prevent many types of common attacks, such as **SQL Injection**, **Cross-Site Scripting (XSS)**, **Remote File Inclusion (RFI)**, and **Cross-Site Request Forgery (CSRF)**.

Core Functions of a WAF

- **Input Validation:** Checks all user inputs like form data, URLs, and query strings to make sure they are safe.
- **Request Filtering:** Analyzes each HTTP request and response to detect suspicious patterns.
- **Traffic Monitoring:** Logs all web activity for analysis and forensic investigations.
- **Blocking Attacks:** Automatically blocks or challenges malicious requests based on predefined or learned rules.
- **Session Protection:** Helps to protect against session hijacking or abuse of authentication tokens.

Types of WAF Deployments

Depending on the system architecture and organization needs, a WAF can be deployed in different ways:

1. Network-Based WAF (Hardware or Virtual Appliance)

A **Network-Based WAF** is usually installed as a dedicated device (hardware or virtual appliance) inside the data center or on the edge of the network. It works by acting as a **reverse proxy**, sitting between the user and the web application server. All traffic goes through the WAF before reaching the application.

Advantages:

- High performance and low latency (especially on dedicated hardware).
- Full control over configurations and policies.
- Good for large enterprises with high traffic.

Disadvantages:

- Expensive hardware and complex setup.
- Needs technical staff for maintenance.
- Not suitable for cloud-native or small environments.

2. Host-Based WAF (Installed on the Web Server)

A **Host-Based WAF** is installed as software on the same server where the web application is hosted. It works closely with the web server (like Apache, Nginx, or IIS) and inspects traffic as it comes in.

Advantages:

- Very customizable to match the specific application.
- No need for extra hardware.
- Often open-source (e.g., ModSecurity).

Disadvantages:

- Uses the same server resources (CPU, memory).
- Harder to manage across many servers.
- Less effective for blocking large-scale attacks (e.g., DDoS).

3. Cloud-Based WAF (As-a-Service)

A **Cloud-Based WAF** is offered by third-party security providers (such as AWS WAF, Cloudflare, or Azure WAF). The company redirects its website traffic through the provider's secure servers. These services inspect traffic and forward only clean requests to the web application.

Advantages:

- Easy to deploy (just change DNS settings).
- Automatically updated to detect the latest threats.
- Scales well with high or changing traffic.

Disadvantages:

- Less control over backend systems and rules.
- May introduce some latency depending on provider location.
- Depends on the third party for reliability and privacy.

Key Capabilities of Modern WAFs

Modern WAFs offer many advanced features to handle both known and unknown web threats:

- **Signature-Based Detection:** Uses a database of known attack patterns (like a virus scanner).
- **Anomaly-Based Detection:** Learns normal traffic behavior and flags anything unusual.
- **Geo-Blocking and IP Reputation:** Blocks traffic from suspicious countries or known bad IPs.
- **Bot Detection:** Differentiates between good bots (like Google crawlers) and bad bots (like credential stuffers).
- **Rate Limiting:** Limits how many requests a user or bot can send per second.
- **SSL Inspection:** Decrypts HTTPS traffic to inspect encrypted attacks.
- **Virtual Patching:** Protects against known vulnerabilities before the app is updated.

AI-Enhanced WAFs

Some newer WAFs, like the one we built in our project, go even further by using **Artificial Intelligence and Machine Learning**. These WAFs can:

- Detect **zero-day attacks** (new threats with no known signature).
- Analyze traffic behavior over time.
- Reduce false positives by understanding context.
- Automatically learn and update protection rules.

Our **AI-based WAF** also includes a **Telegram bot** that sends real-time alerts to the administrator when an attack is detected, making it fast, smart, and practical for modern web applications.

2.4 Artificial Intelligence in Cybersecurity

As cyber threats continue to evolve in complexity, speed, and scale, traditional security mechanisms are no longer sufficient on their own. Most conventional systems rely on manually defined rules, static signatures, or known attack behaviors. While effective against well-documented threats, they struggle to detect novel or adaptive attacks such as zero-day exploits or polymorphic payloads. To address this growing challenge, the cybersecurity industry has increasingly turned toward Artificial Intelligence (AI) to develop more intelligent, adaptive, and automated defense systems.

Artificial Intelligence in cybersecurity refers to the application of advanced computational models that can analyze large volumes of data, identify patterns, detect anomalies, and make real-time decisions without the need for constant human input. AI enhances traditional detection and prevention methods by allowing systems to learn from experience, adapt to new threats, and respond to complex attacks in ways that static rule-based systems cannot.

2.4.1 AI Applications in Cybersecurity

AI is now widely integrated into many areas of cybersecurity, including:

- **Intrusion Detection Systems (IDS):** AI models are used to distinguish between legitimate and malicious activity based on behavioral patterns rather than fixed rules.
- **Threat Intelligence:** AI can process threat data from various sources, correlate indicators, and predict emerging attack trends.

- **Endpoint Protection:** AI enhances antivirus and anti-malware systems by identifying malicious software behavior rather than relying only on signature databases.
- **Fraud Detection:** In financial and e-commerce systems, AI can detect unusual transaction patterns that may indicate fraudulent activity.

In web application security, AI is especially valuable for identifying threats that occur at the application layer, such as injection attacks, session hijacking, bot abuse, and logic-based vulnerabilities.

2.4.2 Core AI Techniques Used in Cybersecurity

There are several machine learning techniques commonly used in intelligent security systems:

- **Supervised Learning:** This method involves training the AI model using labeled data, such as traffic marked as "benign" or "malicious." Once trained, the model can classify new data based on learned patterns.
- **Unsupervised Learning:** Here, the model learns from data that has no labels. It attempts to discover patterns or clusters on its own, which is useful for detecting unknown or zero-day attacks.
- **Clustering:** The algorithm groups similar data together and flags outliers that do not match any group. These outliers may represent suspicious or malicious behavior.
- **Time-Series Analysis:** This technique observes how data or behavior changes over time, making it useful for detecting slow attacks, reconnaissance activities, or brute-force attempts.
- **Reinforcement Learning:** The AI learns through a system of rewards and penalties, improving its decisions over time through continuous interaction with the environment.

Each of these techniques can contribute to developing intelligent security tools that not only react to known threats but proactively identify and respond to new, evolving attacks.

2.4.3 Role of AI in Web Application Firewalls

Web Application Firewalls (WAFs) traditionally rely on rule sets and signatures to detect and block threats. While this approach is effective for known attack patterns, it lacks flexibility and often results in high false positive rates. AI-enhanced WAFs overcome these limitations by analyzing live traffic in real time, learning normal usage patterns, and identifying deviations that may indicate a threat.

For example, an AI-powered WAF can detect:

- Login forms being abused through credential stuffing.
- Hidden SQL queries injected through input fields with altered syntax.
- Bots attempting to scrape data while mimicking user activity.
- Multi-step attack sequences that static rules may miss when analyzed individually.

By learning from both historical and live data, the AI model continuously improves its understanding of the application's behavior. It can identify sophisticated and previously unknown attacks with greater accuracy and speed.

2.4.4 Implementation in Our Project

In this project, we designed and implemented an **Intelligent Web Application Firewall** that uses a machine learning model trained on labeled traffic data, including samples of SQL injection, cross-site scripting (XSS), and normal HTTP requests. The trained model is integrated with the WAF engine to analyze incoming traffic in real time and classify it as either legitimate or malicious.

To enhance response capability, we added a **Telegram Bot integration** that sends immediate alerts to system administrators when a threat is detected. This ensures rapid awareness and allows administrators to respond quickly, even if they are not monitoring the system at that moment.

- **Interpretability:** Some AI techniques, especially deep learning models, can be difficult to interpret, which may reduce trust in automated decisions.

Conclusion

Artificial Intelligence is a transformative force in modern cybersecurity. Its ability to analyze vast datasets, detect anomalies, and learn from evolving behavior makes it an essential component in defending against today's advanced web threats. In the context of our Intelligent WAF, AI enables real-time detection, faster incident response, and greater adaptability—ultimately making web applications more secure and resilient against a constantly changing threat landscape.

2.5 Review of Existing WAF Solutions and Research Gaps

Over the past two decades, Web Application Firewalls (WAFs) have evolved significantly in response to the rising number and sophistication of web-based attacks. Numerous commercial and open-source WAF solutions are available on the market, each offering different capabilities, deployment models, and levels of customization. While these systems have proven effective in many scenarios, they also have limitations—particularly in their ability to detect modern, adaptive, and unknown threats.

2.5.1 Overview of Existing WAF Solutions

1. Commercial WAFs:

Major cloud providers such as AWS WAF, Azure Web Application Firewall, and Google Cloud Armor offer scalable, cloud-native WAF services that integrate directly into their cloud infrastructure. These services typically provide features such as managed rules, bot mitigation, geo-blocking, and DDoS protection. Other commercial vendors like Imperva, F5 Networks, Akamai Kona Site Defender, Cloudflare, and Barracuda offer high-performance, enterprise-grade WAF solutions with advanced threat intelligence and analytics.

2. Open-Source WAFs:

Tools like ModSecurity have gained popularity due to their flexibility and community support. ModSecurity, particularly when combined with the OWASP Core Rule Set (CRS), offers a powerful foundation for custom rule creation and application-layer inspection. Open-source WAFs are widely used for research, prototyping, and small-to-medium scale deployments due to their cost-effectiveness and transparency.

Limitations of Existing Solutions

Despite their capabilities, both commercial and open-source WAFs share some common limitations:

- **Dependence on Static Rule Sets:** Most WAFs rely on signature-based detection and predefined rules. While effective against known threats, these systems are slow to adapt to novel attack techniques or zero-day vulnerabilities.
- **High False Positive Rates:** Static rules often lack contextual awareness. As a result, legitimate traffic may be mistakenly blocked, leading to disruptions in user experience and increased maintenance effort.
- **Manual Configuration and Tuning:** WAFs often require significant effort to customize, update, and tune rules to the specific logic of each

application. This task becomes more difficult as applications grow in complexity.

- **Limited Behavioral Analysis:** Most WAFs do not learn or adapt from user traffic patterns. Without advanced behavioral models, these systems struggle to detect stealthy or evolving threats that do not match traditional attack signatures.
- **Weak Real-Time Response Capabilities:** Many systems detect threats but lack mechanisms for automated, real-time notifications or integration with incident response tools.

Identified Research Gaps

In light of these limitations, several research opportunities exist to enhance the functionality and intelligence of WAF technologies:

1. **Integration of Machine Learning Models:** Incorporating supervised or unsupervised learning techniques can improve detection of unknown or mutated threats by learning from traffic behavior rather than relying only on signatures.
2. **Behavior-Based Detection:** Research into user and session behavior modeling can allow WAFs to identify multi-step or logic-based attacks that static rules may miss.
3. **Low-Latency AI Models:** Developing lightweight, real-time machine learning models that can operate at the application layer without introducing performance overhead remains an open area for optimization.
4. **Automated Alerting and Response Mechanisms:** Integrating WAFs with real-time messaging tools, like Telegram or Slack bots, can provide immediate visibility into attacks and improve the speed of incident response.
5. **Model Explainability and Trust:** AI models used in security must be transparent and interpretable to gain trust from system administrators. Research into explainable AI (XAI) is essential for broader adoption.

Contribution of This Project

This graduation project directly addresses several of these research gaps by implementing an AI-powered Web Application Firewall capable of detecting both known and unknown threats based on learned patterns from historical traffic data. Additionally, the system includes a Telegram Bot integration that

notifies administrators instantly when a threat is detected, enhancing the response time and operational awareness.

Why Traditional Firewalls Are Not Enough for Web Applications ?

Now that we understand the deep level of inspection a WAF performs, it becomes very clear why a traditional firewall, despite being an important security tool, is simply not enough to protect modern web applications. The problem stems directly from its **lack of application-layer awareness**. It cannot see or understand any of the details we just discussed.

Let's revisit our building analogy to make this perfectly clear. The traditional firewall is the guard in the main lobby. The WAF is the expert security detail outside the CEO's office. The lobby guard's job is important, but they are not equipped to stop threats that are designed to attack the CEO directly.

Here is a breakdown of what a traditional firewall *cannot* do:

- **It Cannot Detect Injection Attacks (SQLi, XSS, etc.).** As we've discussed, these attacks are hidden *inside* the content of the HTTP request. The traditional firewall only checks the "envelope" (the IP address and port), not the "letter" inside. An SQL injection attack is written inside the letter. The firewall sees a valid envelope going to a valid address (Port 443) and sends it through, completely unaware of the poison it contains.
- **It Cannot Mitigate Application-Layer DDoS Attacks.** Imagine one hundred different people, all looking like normal visitors, walk into the building lobby. The firewall lets them all in because they came from different places and look legitimate. But then, all one hundred of them run to the single customer service representative (the web application) and start asking very complicated questions all at once. The representative gets completely overwhelmed and has a breakdown (the application crashes). The traditional firewall cannot stop this because, from its perspective, it just looked like 100 normal people entering the building. A WAF, however, can detect this unusual, targeted flood of requests to a specific part of the application and block it.
- **It Cannot Protect Against Business Logic Flaws.** A firewall has absolutely no idea what a "shopping cart," a "user profile," or a "password reset function" is. It is a network traffic cop, not a business

expert. It cannot stop an attacker from using a bug to get a 100% discount on an e-commerce site, because it doesn't understand the application's business rules. A WAF, because it can be configured with more specific rules, can help protect against some of these flaws.

- **It Cannot Enforce Context-Aware Security Policies.** A firewall's rules are very simple: "ALLOW or DENY traffic from IP Address X to Port Y." A WAF's rules can be much, much smarter and more detailed. For example, a WAF can enforce a rule like: "For the URL /api/user/profile, ONLY allow POST requests. The user_id parameter must be an integer, the request must contain a valid session cookie, and we should not see more than 3 requests per second from a single user to this URL." A traditional firewall is incapable of this level of intelligent, context-aware enforcement.

While a network firewall is essential for preventing unauthorized access to your network and blocking a wide range of network-level attacks, it does absolutely nothing to stop a malicious request aimed at exploiting a vulnerability within your web application itself. The request appears perfectly legitimate at the network layer but is highly malicious at the application layer. This is the critical security gap that WAFs are specifically designed to bridge.

Therefore, in today's world, implementing a WAF is **not an optional luxury but a fundamental requirement** for protecting valuable web applications. It provides a necessary and specialized layer of defense that works in concert with, but is distinctly different from, network-level security controls, creating a more complete and resilient security posture.

Chapter 3: System Architecture and Design

This chapter presents the design and architectural structure of the proposed **Intelligent Web Application Firewall (WAF) based on Artificial Intelligence**. It explains how the system components interact, the role of each module, and how data flows between them. The architecture has been carefully designed to ensure real-time traffic analysis, high detection accuracy, and seamless integration with notification systems.

The design decisions in this chapter are based on the identified requirements and limitations discussed in Chapter 2. Key focus areas include modularity, scalability, efficiency, and the ability to detect both known and unknown application-layer threats. To support clarity, various modeling diagrams such as **use case diagrams, context diagrams, data flow diagrams (DFD), sequence**

diagrams, class diagrams, block diagrams, and activity diagrams are included in the following sections.

3.1 Proposed System Overview

The proposed system is an AI-enhanced Web Application Firewall designed to detect and prevent application-layer attacks such as SQL Injection, Cross-Site Scripting (XSS), and other anomalies based on user behavior and request patterns. Unlike traditional WAFs, this system is capable of learning from traffic data and making adaptive decisions without relying solely on static signatures or manual rules.

At a high level, the system consists of the following main components:

- **Traffic Capture and Inspection Module:** Intercepts incoming HTTP/HTTPS requests and extracts relevant features (e.g., headers, parameters, payloads) for analysis.
- **Preprocessing Engine:** Cleans and transforms request data into a format suitable for the machine learning model. This may include normalization, tokenization, and encoding.
- **AI Detection Model:** A machine learning classifier trained to distinguish between benign and malicious traffic based on behavioral and structural features.
- **Rule-Based Policy Layer:** Works alongside the AI model to apply predefined security policies and provide layered protection against known threats.
- **Decision Engine:** Combines outputs from the AI model and rule engine to determine whether to allow, block, or log a request.
- **Alert Notification System:** Sends real-time alerts via **Telegram Bot** to inform administrators when malicious activity is detected.
- **Admin Dashboard (optional):** A simple interface for viewing logs, alerts, and system status.

This architecture allows the WAF to be deployed either as a **reverse proxy in front of the web server** or as a **host-based agent**, depending on the environment. The system is modular, meaning that the AI model can be retrained or replaced without affecting the entire application. Furthermore, the integration of real-time alerting mechanisms significantly enhances the responsiveness of security teams.

3.2 High-Level Architectural Design

The high-level architecture of the proposed Intelligent WAF outlines how different system components interact to provide comprehensive application-layer protection. The design emphasizes modularity, scalability, and real-time detection using a hybrid approach that combines artificial intelligence with traditional rule-based logic.

At the center of the architecture is the **Request Processing Pipeline**, where all incoming traffic is captured and analyzed. The system is divided into multiple interconnected layers, each responsible for a specific function in the security workflow.

Main Architectural Layers:

- 1. Client Layer:**
Represents users (legitimate or malicious) accessing the web application over HTTP/HTTPS. Traffic originates from browsers, bots, or automated tools.
- 2. Firewall Interface (Proxy or Inline Agent):**
Intercepts incoming traffic before it reaches the application server. This component acts as a security checkpoint that forwards request data to the AI engine for analysis.
- 3. Feature Extraction and Preprocessing Module:**
Parses HTTP requests and extracts meaningful features, such as URL parameters, request headers, user-agent strings, and content length. These are cleaned and prepared for input into the AI model.
- 4. AI-Based Detection Engine:**
A pre-trained machine learning model processes the extracted features to classify requests as either **malicious** or **benign**. It learns from historical traffic patterns and continuously adapts to detect unknown threats.
- 5. Rule-Based Detection Engine:**
Works in parallel with the AI engine. Uses predefined signatures and security policies to catch known vulnerabilities (e.g., SQL injection patterns or disallowed file uploads).
- 6. Decision Engine:**
Merges the outputs from both AI and rule-based modules. Based on confidence thresholds and security policies, it decides whether to allow, block, or log the request.

7. **Alerting and Logging Module:**

Sends a real-time notification to administrators via **Telegram Bot** in case of an attack. All requests and decisions are logged for auditing and further analysis.

8. **Web Application Backend:**

The protected resource. It only receives requests that are deemed safe after passing through the WAF system.

This architecture ensures that traffic is fully inspected before reaching the target application, and it allows security decisions to be made using both learned intelligence and static rules. Additionally, the separation of modules makes it easy to update the AI model or add new rules without modifying the entire system.

3.3 Use Case Modeling

Use case modeling is a foundational technique in system design that defines how external actors interact with a system. It helps visualize the system's expected behavior in response to various inputs and user roles. For a security system like the **AI-based Intelligent Web Application Firewall (WAF)**, use case modeling is particularly valuable because it helps illustrate how different types of users (both legitimate and malicious) engage with the system and how the WAF responds to their actions.

This modeling technique helps stakeholders—including developers, administrators, and reviewers—understand the functional boundaries of the system and identify the interactions required to ensure secure operation. Each use case captures a specific system behavior initiated by an actor and describes the expected outcome.

Actors and Their Roles

1. **Legitimate User:**

This is a normal user of the web application, such as a customer or employee, who interacts with the system through standard operations like browsing, submitting forms, or logging in. Their requests should pass through the WAF and be allowed if no malicious behavior is detected.

2. **Malicious Actor (Attacker):**

A person or automated bot attempting to exploit application vulnerabilities. Attackers may perform SQL injections, cross-site scripting (XSS), path traversal, or brute-force login attempts. These

actions are intended to bypass authentication, extract sensitive data, or disrupt application behavior.

3. **System Administrator:**

The administrator is responsible for monitoring the system's status, handling alerts, reviewing logs, updating detection rules, and retraining the AI model if necessary. This role is critical in maintaining and improving the effectiveness of the WAF over time.

4. **Web server**

It is an entity that hosts the web site, WAF, etc., this entity is responsible for processing the request that came from the user or system.

5. **Web site**

this entity is the desired domain from user, can be bank web site, store website, etc., this responsible for show the services needed by the customer

6. **WAF**

this is the main entity that intercept, analyze, connect API to virus total and make logs about anything happening in the website and in case of attack it block the ip and make logs.

7. **Virus total server**

it is a web site that make service like checking the malicious domains, IPs, servers, etc., Helps our WAF in detecting the bad entities earlier

8. **Telegram server**

it is a social media app that enable us to make bots that bot send logs in case of attack occurs, connects the WAF through an API.

Main Use Cases of the Intelligent WAF

1. **Receive and Process HTTP Request:**

The system intercepts each incoming HTTP/HTTPS request before it reaches the web server. This is the first step in all interactions with the WAF.

2. **Connect APIs**

use the Virus total service to early detect the, also connect with telegram to send notification to the admin in case of attack

3. **Extract and Preprocess Features:**

The WAF extracts relevant data from the request, such as URL parameters, headers, request methods, and payloads. This data is cleaned and transformed into a suitable format for the AI model.

4. Analyze Request with AI Engine:

The machine learning model receives the processed request features and performs real-time classification. It determines whether the request is benign or exhibits malicious patterns based on trained behavior.

5. Apply Rule-Based Validation:

In parallel with AI analysis, the WAF applies predefined static rules and signature checks to detect known attack patterns, such as common SQL payloads or restricted file types.

6. Make Final Decision:

The system evaluates the outputs from both the AI engine and rule-based validator. Depending on the decision logic (e.g., confidence score, policy thresholds), the request is either allowed, blocked, or flagged.

7. Trigger Real-Time Notification:

If a request is identified as malicious, the system immediately sends an alert to the administrator via an integrated **Telegram Bot**. The alert includes request details, timestamps, and threat type to allow quick investigation.

8. Log Request and Action:

Regardless of whether the request is accepted or rejected, the system logs the traffic, action taken, and model decision for later review, audit, or retraining.

9. Review and Analyze Logs:

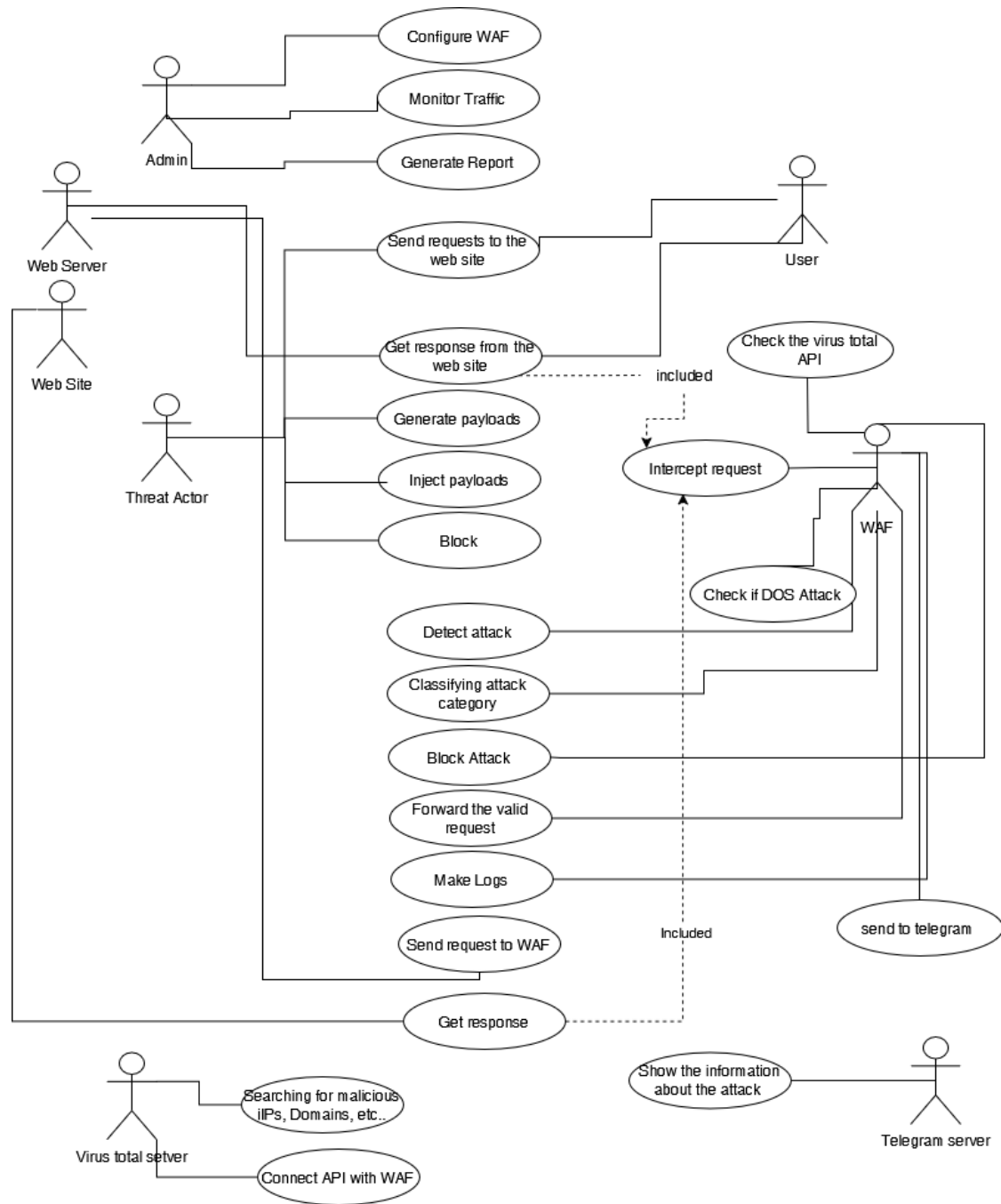
The system administrator periodically accesses logs to study recent traffic, analyze false positives or missed detections, and evaluate the system's performance.

10. Update Detection Policies and Retrain Model:

The administrator can update static rules or provide new training data to the AI engine. This allows the WAF to adapt to emerging threats and improve detection accuracy over time.

Importance of Use Case Modeling

Use case modeling ensures that the system is functionally complete, robust, and aligned with user expectations. It highlights critical flows, such as how the system distinguishes between safe and malicious traffic, and how alerts are delivered in real time. This model also guides development and testing teams by providing a functional blueprint of the Intelligent WAF system.



3.4 Context Diagram

A context diagram is a high-level visual representation that shows how the system interacts with external entities. It outlines the system's boundaries, its main components, and the flow of information between the system and its environment. This type of diagram is especially useful in complex systems where multiple actors and data sources are involved.

For the AI-Based Intelligent Web Application Firewall (WAF), the context diagram illustrates how external users, attackers, administrators, and the protected web application interact with the firewall system. It also highlights the role of the AI engine and alerting mechanism, showing clearly what enters and exits the system at the top level.

Purpose of the Context Diagram

The main purpose of this diagram is to:

- Define the system's scope.
 - Clarify the interactions between external users and the WAF.
 - Show the direction and types of data flowing in and out.
 - Identify the main actors without exposing internal processing complexity.
-

System Boundary: Intelligent WAF

The Intelligent WAF system is placed at the center of the context diagram. It acts as a protective layer between external users and the internal web application. It inspects, classifies, and decides on each HTTP/HTTPS request before it reaches the server.

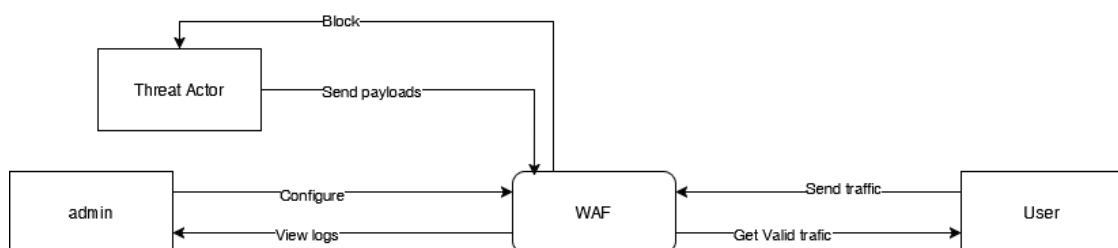
External Entities and Their Interactions

1. Client (Legitimate User):
This represents any real user accessing the web application through a browser or mobile device.
 - Sends: HTTP/HTTPS requests (login, search, form submissions, etc.).
 - Receives: Responses from the web server (e.g., web pages, data).
2. Malicious Actor (Attacker):
A person or bot attempting to exploit vulnerabilities in the application (e.g., using SQL Injection, XSS).
 - Sends: Malicious requests that may appear normal but contain harmful payloads.

- Receives: Either a blocked response or a generic denial message from the WAF.
3. **Web Application (Protected Resource):**
The backend system that handles legitimate user requests, including business logic, database access, and page generation.
- Receives: Clean, filtered requests from the WAF.
 - Sends: Valid responses to clients if the request is allowed.
4. **System Administrator:**
A security operator who monitors the system and manages configurations.
- Receives: Real-time attack alerts via Telegram Bot.
 - Sends: Updates to rules or AI model when necessary.
5. **Telegram Notification Service:**
This external integration delivers immediate alerts to the system administrator's device when an attack is detected.
- Receives: Alert messages generated by the WAF engine.
 - Delivers: Instant notifications to Telegram users.

Main Data Flows

- **User Request Flow:**
Clients (both legitimate and malicious) send web requests → WAF intercepts and analyzes them → Clean requests are forwarded to the web application → Response is returned to the user.
- **Threat Detection Flow:**
WAF applies AI analysis + rule-based logic → Malicious requests are blocked → Alerts are sent to the Telegram bot.
- **Administrative Flow:**
Admin reviews logs and receives alerts → Admin can update rules or retrain the AI model as needed.



3.5 Data Flow Diagram (DFD)

A Data Flow Diagram (DFD) is used to model how data moves through a system. It breaks down the system into functional components and visually represents the inputs, outputs, data stores, and processing steps involved in each part of the system. The purpose of a DFD is to provide a clear and structured understanding of how data is handled at various levels of the system.

For the AI-Based Intelligent Web Application Firewall (WAF), the DFD describes how HTTP requests are intercepted, analyzed, and processed through both AI and rule-based engines before being passed to the web application or blocked.

Purpose of the DFD

The DFD helps developers, security analysts, and stakeholders understand:

- How user input (web requests) is processed inside the WAF.
- What decisions are made at each stage of traffic inspection.
- How data such as logs and alerts are generated and where they are stored or sent.
- How the WAF system integrates with external components like the web server and Telegram Bot.

Level 0 DFD – System Overview

At Level 0, the Intelligent WAF is treated as a single process. It receives traffic from external users and attackers, filters it, and sends allowed traffic to the protected web application.

External Entities:

- Client (User)
- Attacker
- Administrator
- Web Application
- Telegram Bot

Process:

- Intelligent WAF System

Data Flows:

- Incoming HTTP requests (from users and attackers)
 - Outgoing responses (to users)
 - Allowed requests (to web app)
 - Alerts (to admin via Telegram)
 - Log data (stored for analysis)
-

Level 1 DFD – Internal Workflow of the WAF

The Level 1 DFD breaks down the WAF into its core functional components.

The following processes are modeled:

1. P1: Request Interception
 - Captures every incoming HTTP/HTTPS request before it reaches the web application.
 - Forwards the request for analysis.
2. P2: Feature Extraction & Preprocessing
 - Parses and processes request data (headers, payloads, URLs).
 - Prepares it for AI classification and rule-based inspection.
3. P3: AI Model Evaluation
 - Applies the machine learning model to classify traffic as benign or malicious.
 - Outputs confidence scores or classifications.
4. P4: Rule-Based Filtering
 - Applies predefined WAF rules to detect known threats (e.g., SQLi, XSS patterns).
 - Flags matching requests.
5. P5: Decision Engine
 - Combines results from AI and rule engine.

- Decides to allow, block, or log the request.

6. P6: Alert Generation

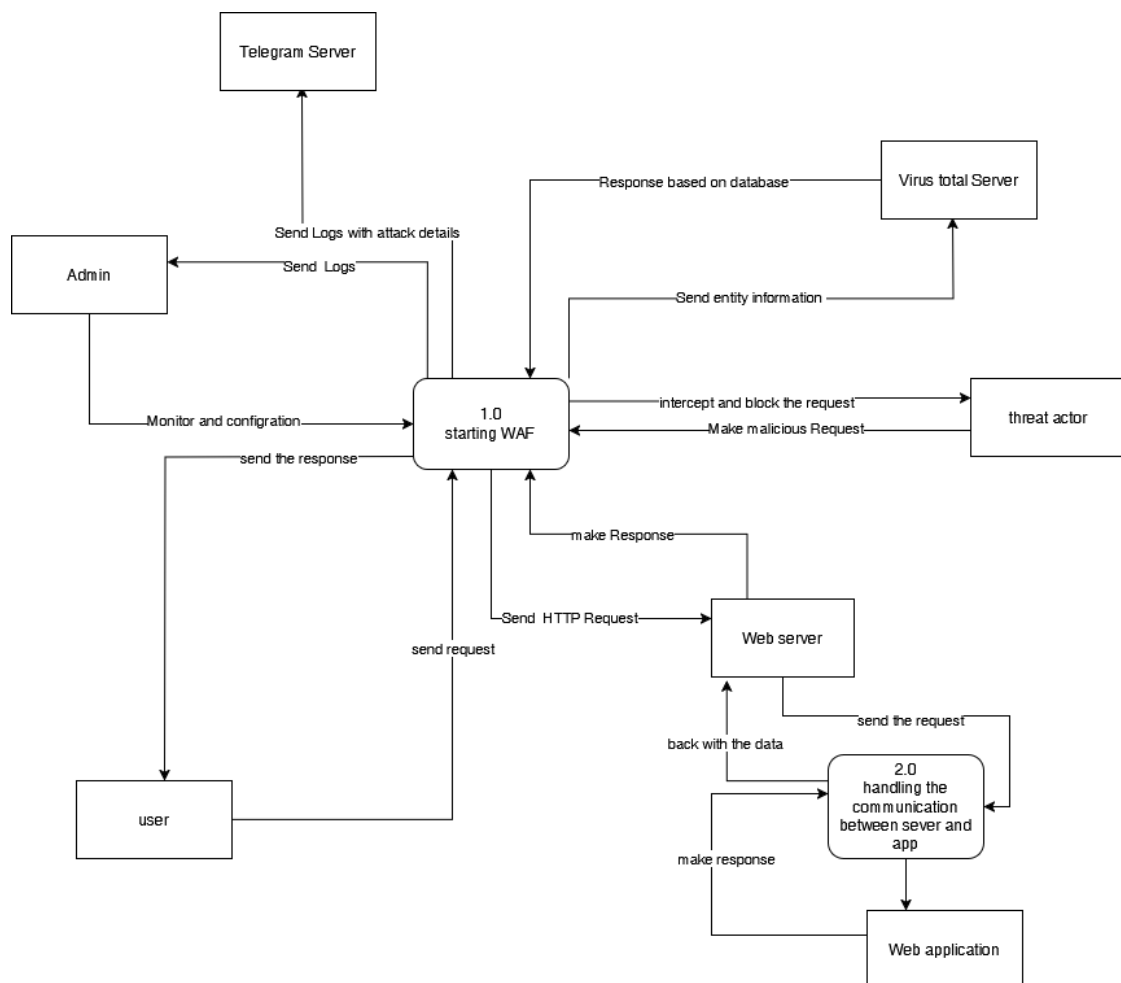
- If a threat is detected, an alert is created and sent to the Telegram bot.

7. P7: Logging & Storage

- Stores request logs, AI results, decisions, and alerts for later review.

Data Stores:

- D1: Log Database – Stores all processed request logs and decisions.
- D2: AI Training Data – Stores training datasets used to retrain or improve the AI model.
- D3: Static Rule Set – Contains the predefined WAF rules.



3.6 Sequence Diagram

A Sequence Diagram is a type of UML (Unified Modeling Language) diagram that shows how objects or components in a system interact with each other over time. It focuses on the sequence of messages exchanged between system modules or actors during the execution of a specific use case. This helps in understanding the dynamic behavior of the system, especially the timing and order of events.

For the AI-Based Intelligent Web Application Firewall (WAF), the sequence diagram models the interaction flow that occurs when a user (legitimate or malicious) sends a request to the web application, and how the WAF handles, analyzes, and responds to that request.

Purpose of the Sequence Diagram

- To visualize the order in which system components interact in real time.
- To show the step-by-step execution of the request analysis process.
- To describe the internal workflow of the WAF system clearly and sequentially.
- To support developers in implementing and testing system logic.

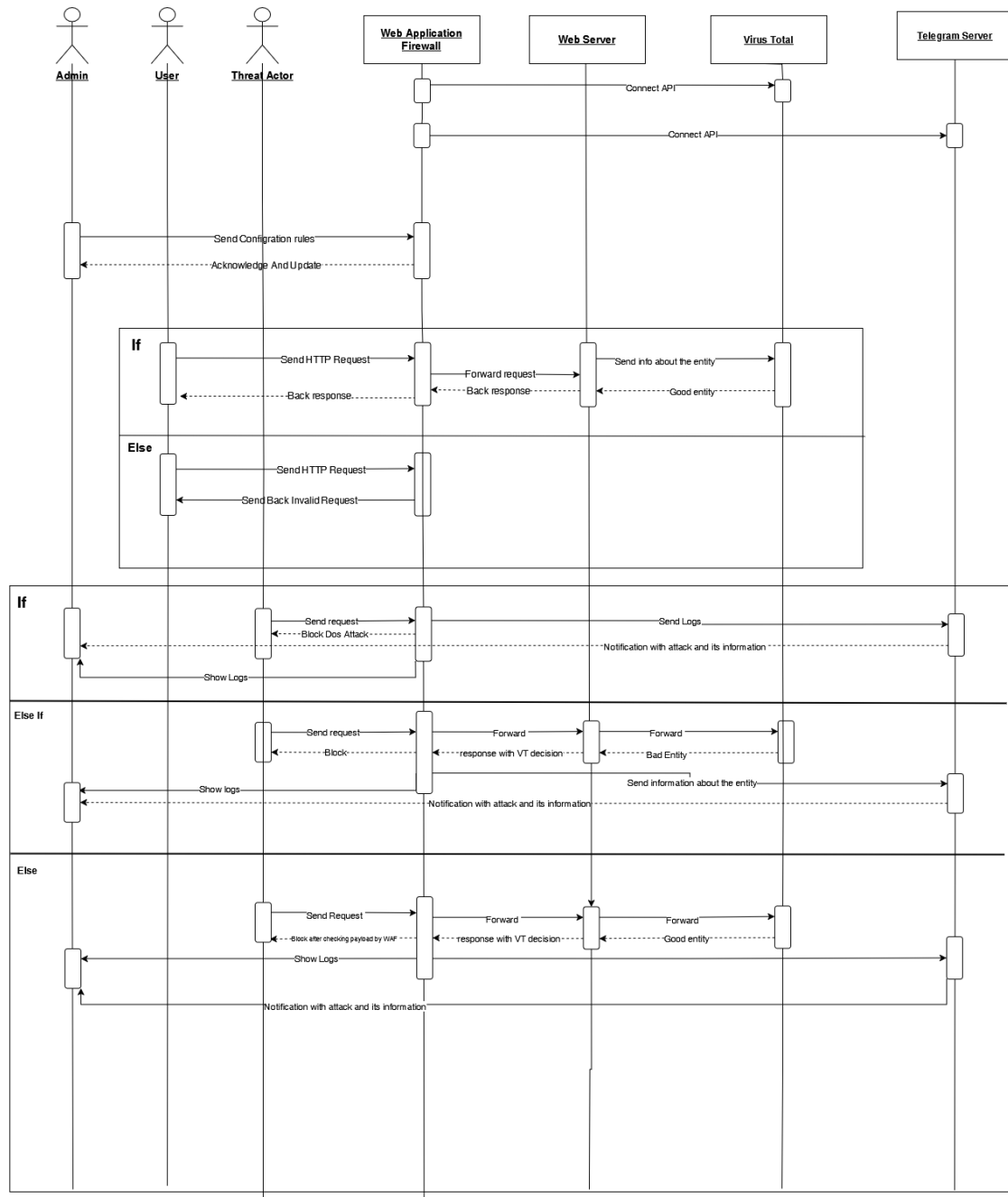
Main Objects in the Sequence

1. Client (User or Attacker):
Initiates the request by accessing the web application over HTTP/HTTPS.
2. Web Application Firewall:
Intercepts the incoming request before it reaches the backend application.
3. Admin:
Configure WAF as business requirements.
4. Virus Total Server:
Connect with API with WAF, Help WAF to detect The user it self is bad, malicious, or an automated tool (super power human) based on IPs.

5. Telegram Notification Service:
If a threat is detected, the system sends a real-time alert to the administrator.
 6. Web Application Server:
Processes clean requests that pass WAF inspection and sends responses back to the client.
-

Sequence of Interactions

1. Admin Configure the WAF based on Business requirements
2. Connect APIs
3. Client sends HTTP/HTTPS requests to the application.
4. Firewall Interface intercepts the request before it reaches the backend.
5. Check if It an DOS Attack, If it is not will pass else will be blocked.
6. Check if it good it will be passed to the webserver.
7. If it is not good due to incorrect username password, send back until it sends it correct.
8. Send the Entity's information to the virus total solution.
9. Virus total response to the WAF about it.
10. If bad entity it blocked and added to blacklist and send notification, if good.
11. Based on virus total:
 - If good back to the WAF and it will analyze the request if bad block and add to blacklist and send notification via telegram bot to the administrator and show on the GUI of the WAF solution.
 - Else confirm as bad entity from virus total it will be blocked and added to blacklist.
12. At the end all activities is logged and showed to admin in the admin panel.



3.7 Class Diagram

A Class Diagram is a structural UML diagram that describes the internal design of a system by modeling its classes, their attributes, methods (operations), and relationships with other classes. It provides a static view of the system architecture and is particularly useful for developers during implementation, as it clearly defines how different components of the system are organized and interact with each other.

In the context of the AI-Based Intelligent Web Application Firewall (WAF), the class diagram represents the key components involved in request analysis,

decision-making, alerting, and logging. Each class corresponds to a specific module or functional unit in the system, encapsulating its data and behavior.

Purpose of the Class Diagram

- To define the system's internal structure at the code and module level.
 - To illustrate object-oriented design principles, such as encapsulation and modularity.
 - To show how data and operations are grouped into logical units.
 - To support maintainable and scalable development.
-

Key Classes in the WAF System

1. Admin

- Attributes: IP, Username, Password, Session ID
- Methods: Configure_WAF(), Block_UnBlock(), Traffic_Monitoring()

2. User

- Attributes: IP, Username, Password, Session ID
- Methods: receive_response(), make_request()

3. Threat Actor

- Attributes: IP, Session ID
- Methods: Generate_malicious_Request(), Receive_Response (X1: Request).

4. Virus total

- Attributes: IP, Database, API, Session ID.
- Methods: Searching_In_DataBase(), Connect_API (), Verify_The_entity ()

5. Web application

- Attributes: Requests
- Methods: Genetrade_Traffic()

6. Web Server

- Attributes: IP, database, WAF IP, Web sites IP
- Methods: hosting(), exportLogs(),
send_request_to_waf(x1:request)

Records all request data, decisions, and system events for audit purposes.

7. WAF

- Attributes: AI model, IP, Request, Logs, DataSet
- Methods: Forward(), generate_logs(), block(), classification(),
connect_API(), Intercepting()

Sends real-time alerts via Telegram Bot when a threat is detected.

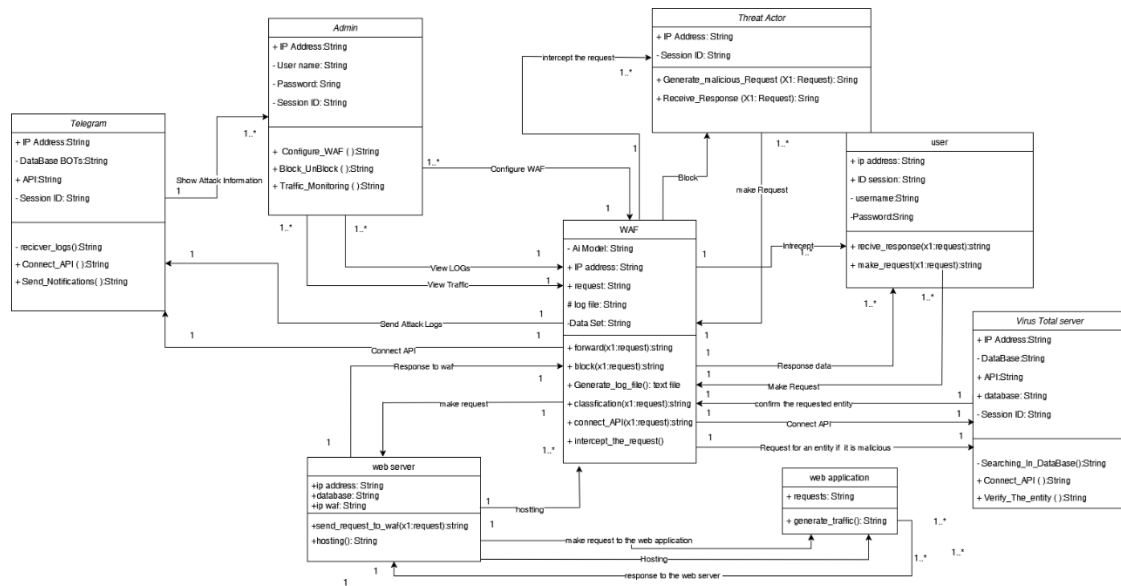
8. Telegram

- Attributes: IP, Database BOTs, API, Session ID
- Methods: reciever_logs(), Connect_API (), Send_Notifications()

Responsible for monitoring, updating, and maintaining the WAF system.

Relationships and Associations

- WAF is the central entity interacts with all
- DecisionEngine depends on both WAF and Viruse Total outputs.
- AlertNotifier is activated by WAF and Telegram in case of detected threats.
- Logger receives input from all modules to maintain complete records.
- Administrator interacts with WAF and Telegram.



3.8 System Block Diagram

A System Block Diagram provides a simplified visual representation of a system's architecture, focusing on the key components (or modules) and how they are logically connected. It is typically used to communicate the high-level structure of the system to both technical and non-technical stakeholders. Unlike class diagrams, which focus on internal object relationships, the block diagram highlights how different parts of the system function together as a whole.

For the AI-Based Intelligent Web Application Firewall (WAF), the block diagram outlines the flow of data and control between major components—starting from the interception of incoming traffic to the final delivery (or blocking) of HTTP requests. It also shows how alerts and logs are generated and where administrative actions may take place.

Purpose of the System Block Diagram

- To present a simplified yet complete view of the system's functional architecture.
- To help understand how different modules interact in a real-time WAF environment.
- To guide implementation and integration across modules.
- To support communication of system logic during design reviews or presentations.

Main Blocks in the Intelligent WAF Architecture

1. **User/Attacker:**
Initiates an HTTP or HTTPS request by interacting with the web application.
2. **Traffic Interception Layer (Firewall Interface):**
Acts as the first point of contact. Captures all incoming traffic and redirects it to the inspection engine.
3. **Preprocessing & Feature Extraction Block:**
Breaks down each request into structured elements like headers, query parameters, and payloads. Converts these into feature vectors for further analysis.
4. **Virus Total Solution:**
Uses a database of all possible known entities such as IPs, Domains, Locations, etc...
5. **AI Threat Detection Module:**
Uses a pre-trained machine learning model to classify traffic based on behavior and structure. Produces a confidence score indicating whether the request is benign or malicious.
6. **Rule-Based Analysis Module:**
Performs static pattern matching using a set of predefined rules. Quickly identifies known vulnerabilities (e.g., common SQL injection strings).
7. **Decision Logic Unit:**
Consolidates results from both AI and rule-based modules. Based on policy thresholds, determines if a request should be allowed, blocked, or logged.
8. **Telegram Alert Service:**
If a threat is identified, this module formats the threat information and pushes it as a real-time alert to the administrator via a Telegram Bot.
9. **Logging & Storage:**
Maintains a complete record of all processed requests, system decisions, threat scores, and alert actions for auditing and model improvement.

10. Administrator Interface:

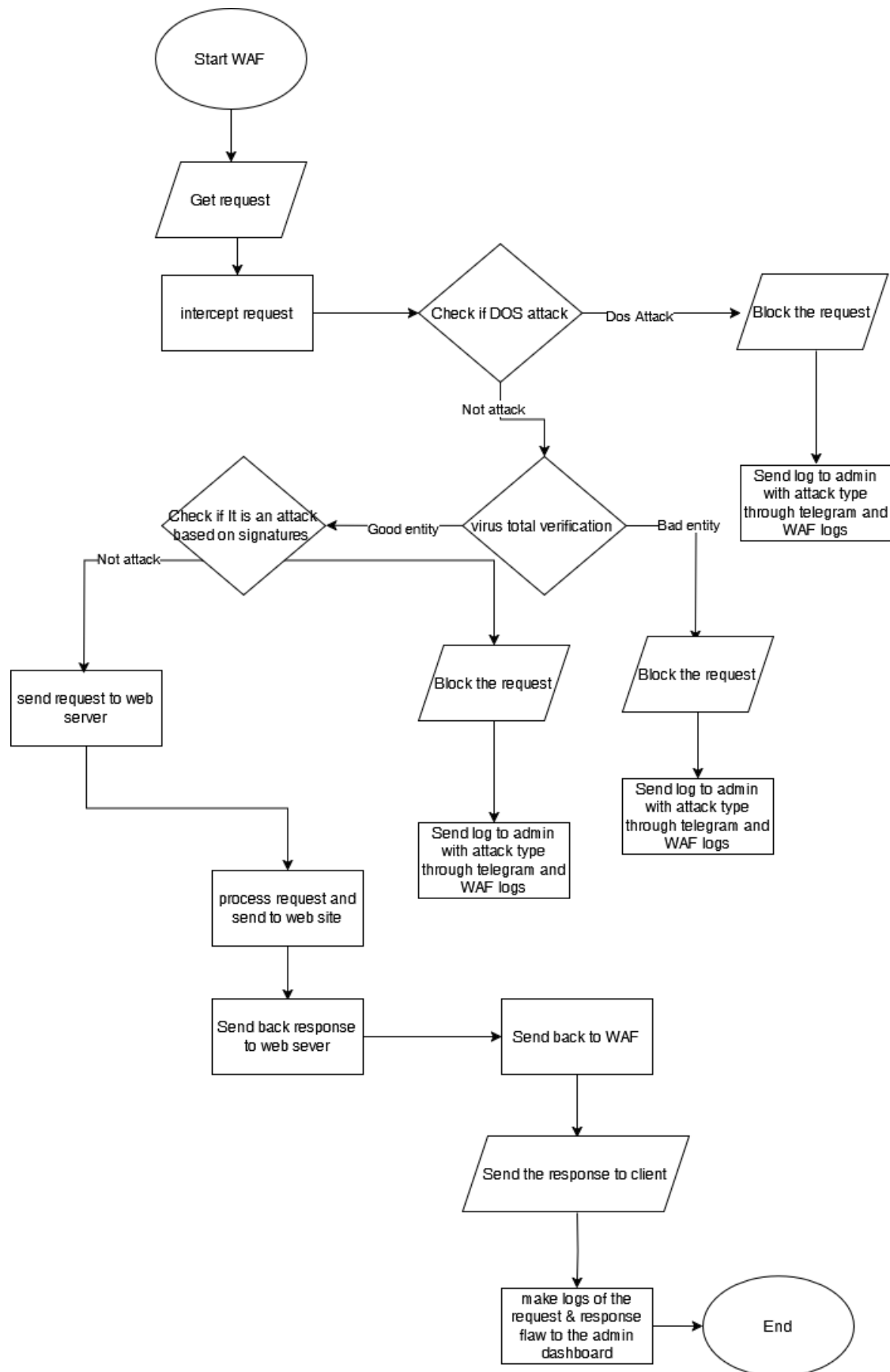
Allows the system administrator to monitor logs, view threat notifications, retrain the AI model, and update detection rules.

11. Web Application (Backend):

The protected server. Only receives requests that have been classified as safe by the WAF system.

System Flow Summary

1. A user (or attacker) sends a request.
2. Identify it is DOS Attack??
3. Get confirmation form Virus total solution
4. The request is intercepted and passed to the preprocessing block.
5. Features are extracted and analyzed in parallel by the AI and rule engines.
6. The decision logic determines the outcome.
7. If the request is clean, it is forwarded to the web application.
8. If malicious, it is blocked and an alert is sent.
9. All results are **logged for future review and training.**



3.9 Activity Diagram

An Activity Diagram is a behavioral UML diagram that models the dynamic workflow of a system. It represents the sequence of activities (or actions) performed by the system in response to inputs, including decision points, parallel processes, and the overall control flow. It is especially useful in systems like a Web Application Firewall, where actions must be taken quickly and conditionally based on traffic analysis.

For the AI-Based Intelligent Web Application Firewall (WAF), the activity diagram illustrates the step-by-step flow of how an incoming request is handled—from the moment it is intercepted, to the point where it is either passed to the web server, blocked, or logged and alerted.

Purpose of the Activity Diagram

- To describe the logical flow of control during WAF operation.
- To capture system behavior during request inspection and decision-making.
- To clarify how conditional decisions (malicious vs. benign) affect the request path.
- To support implementation and testing by visualizing process logic.

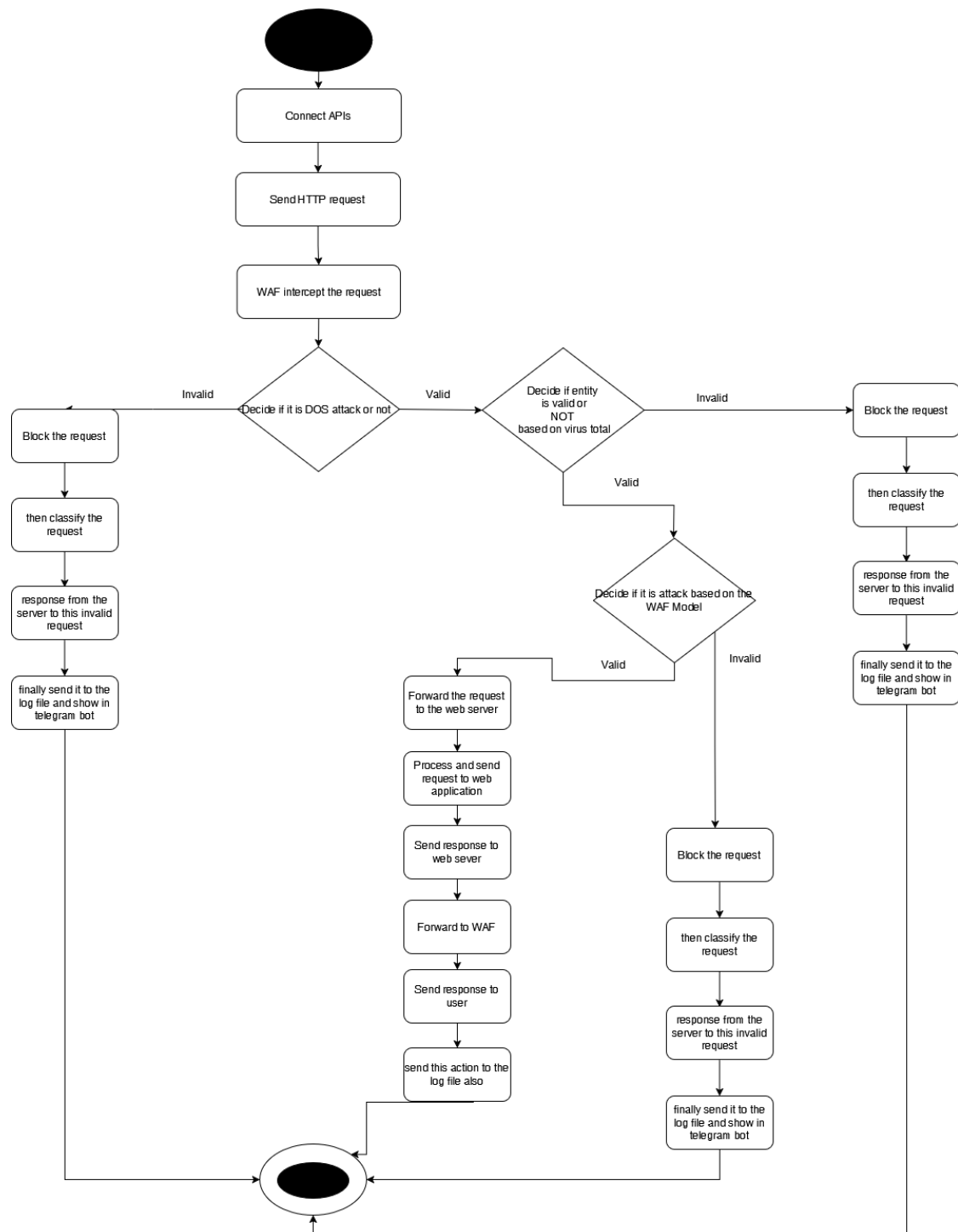
Workflow Overview

1. Start
The system is running and waiting to receive incoming HTTP or HTTPS traffic.
2. Intercept Request
A new request arrives and is intercepted by the WAF proxy or agent.
 - Ask Virus total solution
send to virus total solution entities and get back response
If Malicious:
 - a. Block the request.
 - b. Log the event.
 - c. Send a real-time alert to the administrator via Telegram.
 - If Benign:
 - a. Forward the request to the backend web application.
 - b. Log the event.

3. Extract Features
Request components (URL, headers, parameters, payload) are parsed and formatted.
 4. Run AI Detection
The extracted features are passed to the machine learning model for threat evaluation.
 5. Run Rule-Based Detection (Parallel Process)
Simultaneously, the system checks the request against a predefined set of security rules.
 6. Merge Detection Results
The outputs from the AI and rule-based detection engines are merged for evaluation.
 7. Make Decision
The Decision Engine applies logic (e.g., threshold comparison, confidence scoring) to classify the request.
 - If Malicious:
 - a. Block the request.
 - b. Log the event.
 - c. Send a real-time alert to the administrator via Telegram.
 - If Benign:
 - a. Forward the request to the backend web application.
 - b. Log the event.
 8. End
The system resumes idle state, awaiting the next request.
-

Key Decision Points

- Is the Request Malicious?
This is the core conditional branch in the diagram. Based on combined detection results, the system determines the path the request will follow.
- Should an Alert Be Sent?
If the threat level exceeds a defined threshold, an alert is immediately **pushed to the administrator**.



Chapter 4: System Implementation and Training

This chapter explains the practical realization of the proposed **AI-Based Intelligent Web Application Firewall (WAF)**. After presenting the theoretical foundation and architecture design in previous chapters, this section focuses on how each component of the system was developed, configured, and integrated into a functional prototype. It covers both software and machine learning aspects of the project, ensuring that the WAF is capable of inspecting web requests, detecting malicious behavior, and responding to threats in real-time.

The implementation process was divided into multiple stages. These included the setup of the development environment, preparation and labeling of datasets, training and validation of the AI model, and the construction of the WAF's backend using Python and Flask. In addition, the chapter describes how rule-based detection logic was implemented in parallel with the AI engine to form a hybrid security model, improving detection accuracy and minimizing false positives.

A significant part of the system's intelligence comes from the machine learning model. For that reason, special attention was given to dataset quality, feature engineering, and evaluation metrics. The model was trained using real and synthetic traffic data containing both legitimate and malicious requests. After training, the model was integrated into a lightweight HTTP inspection service that evaluates each incoming request before allowing it to reach the web server.

To improve administrator response time and usability, a **Telegram Bot** was also implemented and connected to the WAF. Whenever an attack is detected, the system sends a detailed real-time alert to the administrator, providing visibility into the nature and origin of the attack. This feature allows faster decision-making and proactive security measures.

The implementation also included a logging mechanism, which stores each request, decision outcome, AI confidence score, and whether an alert was triggered. These logs are useful not only for auditing but also for retraining the model with updated traffic patterns in the future, enabling continuous improvement.

Overall, this chapter demonstrates how theory was translated into practice, highlighting each development step with the tools and methods used. The final system is a fully functional WAF that can operate as a security layer in

front of any web application, providing dynamic, intelligent protection against a wide range of application-layer threats.

4.1 Development Environment and Tools

The successful implementation of a secure, real-time, and intelligent Web Application Firewall (WAF) system requires the careful selection of an appropriate development environment, tools, and technologies. This section outlines the hardware, software, programming languages, and libraries used during the development phase of the project. The choices made were driven by the system's core requirements: high-speed request handling, machine learning integration, alerting capabilities, modularity, and ease of deployment.

The implementation process was carried out on a modern workstation configured to support both machine learning training and web service development. A combination of open-source tools and industry-standard libraries were used to ensure compatibility, transparency, and extensibility of the system components. The development environment was structured to allow for isolated testing of each module, including the AI engine, rule-based engine, Telegram alert system, and HTTP traffic processing API.

4.1.1 Programming Language: Python

Python 3.10 was selected as the primary development language for several reasons:

Wide Ecosystem: Python offers a rich ecosystem of packages for machine learning, web development, data processing, and network communication, which allowed seamless integration of various components without relying on external or proprietary tools.

Rapid Prototyping: Python's concise syntax and interpretability helped accelerate the prototyping and debugging of the system.

Machine Learning Support: Libraries like Scikit-learn, Pandas, and NumPy are natively supported in Python and offer optimized functions for data preprocessing, model training, and evaluation.

All code was written and maintained using Python 3.10, which ensured compatibility with the latest versions of third-party libraries used in the project.

4.1.2 Core Libraries and Frameworks

The table below summarizes the key Python libraries and frameworks used during implementation, grouped by functionality:

Purpose	Tool/Library	Description
Machine Learning	Scikit-learn	Used for training the classification model (Logistic Regression).
Data Preprocessing	Pandas, NumPy	Used for handling and transforming structured traffic data into usable formats.
Web Server/API Backend	Flask	Provides HTTP endpoints for traffic inspection and system operations.
HTTP Simulation & Testing	Requests, Postman	Used to send test HTTP requests to the WAF for evaluation and validation.
Real-Time Notification	python-telegram-bot	Sends alerts to the system administrator via Telegram bot.

All libraries were installed and managed using pip, and their versions were recorded in a requirements.txt file for reproducibility and deployment.

4.1.3 Integrated Development Environment (IDE)

Visual Studio Code (VS Code) was used as the main IDE. It provided:

Syntax highlighting and code linting for Python.

Git integration for version control.

Virtual environment support for dependency isolation.

Extensions such as Jupyter Notebook for exploratory data analysis.

4.1.4 Hardware and Operating System Setup

The system was developed and tested in both Windows and Linux environments to ensure cross-platform compatibility:

Development Machine:

Processor: Intel Core i5 (10th Gen)

RAM: 8 GB DDR4

Storage: 256 GB SSD

OS: Windows 11 (Development) and Ubuntu (Testing)

Local Testing Server:

A lightweight Flask server was deployed on localhost during testing to simulate a real web application behind the WAF.

This setup ensured sufficient processing power for local training of lightweight ML models and testing of live request handling with minimal latency.

4.1.5 Environment Configuration and Version Control

A dedicated virtual environment was created using venv to manage dependencies independently of the system's global packages.

Source code was organized into modular Python packages, following best practices for maintainability.

Git was used as the version control system to track changes and allow safe rollbacks during testing.

4.2 Dataset Preparation and Labeling

The performance and reliability of any machine learning-based system are directly influenced by the quality and relevance of the data used during the training phase. In the case of the Intelligent Web Application Firewall (WAF), it was critical to prepare a dataset that accurately reflects real-world traffic, including both legitimate and malicious HTTP requests. This section outlines the process of collecting, preparing, cleaning, and labeling data used to train the system's classification model.

The dataset preparation phase included multiple stages: sourcing traffic samples, identifying and extracting relevant features, applying data cleansing methods, and assigning correct labels for supervised learning. The resulting dataset served as the foundation for training the AI engine to distinguish between benign and harmful requests with a high degree of accuracy.

4.2.1 Data Collection and Sources

To create a representative dataset, we collected both normal and malicious HTTP request samples from multiple sources:

- Benign Requests:
 - Captured using Postman and browser activity on a local Flask-based demo web application.
 - Simulated typical user actions such as login, registration, form submissions, and search queries.
 - Included standard HTTP methods (GET, POST), headers, parameters, and payloads.
- Malicious Requests:
 - Manually crafted based on common attack patterns, including:
 - SQL Injection: ' OR 1=1 --, UNION SELECT, DROP TABLE
 - Cross-Site Scripting (XSS): <script>alert('XSS')</script>
 - Command Injection: ; rm -rf /, && whoami
 - Path Traversal: ../../etc/passwd
 - Also sourced from:
 - OWASP WAF test corpus
 - Public datasets on GitHub and Kaggle containing labeled web attack logs

A balanced dataset was constructed to ensure the model receives equal exposure to both classes during training.

4.2.2 Feature Selection and Representation

Each HTTP request was processed to extract the following key attributes:

- Request Method (GET, POST, etc.)
- URL path and query parameters
- Request headers (e.g., User-Agent, Content-Type)
- Body content or payload (form values, JSON, etc.)
- Special characters or suspicious patterns (' , < , ; , etc.)
- Length of payload or total content size
- Encoding and content type

These features were then transformed into numerical or categorical representations using encoding techniques such as:

- Tokenization
- One-hot encoding (for method and content-type)
- Vectorization of text-based input (e.g., payload and parameters)

The feature set was standardized across all samples to maintain uniform input dimensions for the machine learning model.

4.2.3 Data Cleaning and Normalization

To improve model performance and reduce noise in the dataset, preprocessing and cleaning were applied:

- Lowercasing: All text inputs were converted to lowercase to avoid duplication by case sensitivity.
- Character Filtering: Non-ASCII and irrelevant special characters were removed.
- Whitespace Normalization: Multiple spaces, tabs, and newline characters were stripped.
- Missing Values: Empty fields were filled with zero vectors or marked as "NA".

These steps helped reduce inconsistencies and ensure clean, structured inputs for both training and testing phases.

4.2.4 Labeling Strategy

Each request sample was assigned a binary label based on its intent:

- 0 – Benign (Safe) request
- 1 – Malicious request

Labeling was performed manually during the simulation process and automatically when using verified external datasets. In total, approximately:

- 1,000 benign samples and
 - 1,000 malicious samples
- were used to build a balanced dataset of 2,000 samples. This balanced approach helped prevent bias toward one class and allowed the classifier to learn clear decision boundaries.

4.2.5 Dataset Structure and Storage

The final dataset was stored in a CSV (Comma-Separated Values) file with the following columns:

Each row represents a single HTTP request converted into machine-readable format and tagged with its respective classification label.

4.3 AI Model Training

The foundation of the proposed Intelligent Web Application Firewall (WAF) lies in its ability to accurately identify malicious behavior in HTTP requests using artificial intelligence. Unlike traditional firewalls that depend solely on signature matching and static rules, our system leverages a supervised machine learning model trained on real and simulated web traffic to detect patterns indicative of application-layer attacks. This section presents the detailed steps involved in designing, training, validating, and integrating the machine learning component into the WAF system.

The goal was to build a classifier capable of distinguishing between legitimate and malicious requests in real time, even when those requests do not match predefined rules. This required the development of a robust, efficient, and lightweight model that could operate with minimal computational overhead while maintaining high detection accuracy.

4.3.1 Model Selection

The model selected for this project was Logistic Regression, a widely used algorithm for binary classification tasks. It was chosen for several key reasons:

- **Simplicity and Speed:** Logistic Regression is fast to train and test, which is ideal for systems that must make decisions quickly, such as firewalls operating in real-time.
- **Interpretability:** Unlike black-box models like neural networks, Logistic Regression produces output in the form of probabilities. This makes it easier to understand and explain why a particular request was classified as malicious or benign.
- **Scalability:** The model can be retrained and deployed easily as new data becomes available, which supports continuous learning and adaptation.
- **Regularization Support:** It allows regularization techniques (L1/L2) to avoid overfitting when working with limited or noisy data.

Alternative models considered included Decision Trees, Random Forests, and Support Vector Machines (SVMs). While these models can achieve high accuracy, they often require more processing power or produce less interpretable results. For the scope of this project, where real-time performance and explainability are essential, Logistic Regression proved to be the most balanced choice.

4.3.2 Training Process

The training process was carefully structured and included the following phases:

1. DATA SPLITTING

- The final dataset (prepared in Section 4.2) consisted of both benign and malicious request samples.
- It was divided into:
 - Training Set (80%) – Used to train the model.
 - Testing Set (20%) – Used to validate the model's performance on unseen data.
- Stratified sampling ensured that both classes were evenly represented in each set to avoid bias.

2. Feature Engineering

To convert raw HTTP request data into a format suitable for training:

- Text fields (such as payloads and URLs) were tokenized and vectorized using frequency-based encodings.
- Categorical data (like request methods or content types) were one-hot encoded.
- Numerical values such as payload length and the count of special characters were included as scalar features.
- The resulting feature vectors contained both lexical and structural indicators of potential attacks.

3. Model Training

- The `LogisticRegression()` classifier from Scikit-learn was instantiated with default parameters.
- Initial training was done using basic hyperparameters.
- Further tuning was performed for:
 - `C` (inverse of regularization strength): Lower values strengthen regularization to prevent overfitting.
 - `Penalty`: L2 regularization was used to ensure smooth model weights.

The final model was trained using the `fit()` method and evaluated iteratively to improve performance.

4. Model Serialization

Once the model achieved satisfactory results, it was saved using:

```
python
```

This allowed the model to be loaded during runtime by the Flask application, eliminating the need to retrain on every execution.

4.3.3 Model Evaluation and Metrics

A critical step in building a reliable machine learning system is the evaluation of model performance. The following metrics were used to validate the classifier:

<i>Metric</i>	<i>Definition</i>
<i>Accuracy</i>	Total correct predictions / total predictions. Reflects general performance.
<i>Precision</i>	$TP / (TP + FP)$. Measures the proportion of predicted attacks that were correct.
<i>Recall</i>	$TP / (TP + FN)$. Measures how many actual attacks were detected.
<i>F1 Score</i>	Harmonic mean of precision and recall. Balances false positives and negatives.
<i>Confusion Matrix</i>	Breakdown of TP, FP, TN, FN to evaluate specific error types.

Results from testing set:

- Accuracy: 99.6%
- Precision:
 - Macro average: 98%
 - Wiegthed average: 100%
- Recall:
 - Macro average: 88%
 - Wiegthed average: 100%
- F1 Score
 - Macro average: 91%
 - Wiegthed average: 100%

4.4 WAF Backend Implementation

The backend implementation of the Intelligent Web Application Firewall (WAF) serves as the operational core of the system. It is responsible for receiving HTTP requests, extracting features, applying detection logic (AI-based and rule-based), and taking appropriate actions such as allowing, blocking, logging, or alerting. This section describes how the backend was developed, the technologies used, its modular structure, and how it integrates all components into a unified and functional system.

The backend was developed in Python using the Flask web framework, chosen for its simplicity, performance, and strong support for building RESTful APIs. The backend functions as a standalone service that intercepts incoming requests before they reach the protected web application. Each intercepted request is processed through a pipeline of analyzers and decision modules to ensure comprehensive inspection and protection.

4.4.1 Flask Web Framework

Flask is a micro-framework in Python designed for rapid web development. It offers:

- Lightweight routing for handling HTTP requests.
- Integration with external modules such as Scikit-learn (for AI), JSON handling, and environment variable management.
- Minimal overhead, making it suitable for high-performance use cases like request filtering and inspection.

The WAF backend was implemented as a Flask application running on a custom port (e.g., 5000), which receives HTTP traffic from a proxy or redirect.

4.4.2 Key Functional Modules

The backend consists of several modular components, each with a distinct responsibility. These modules were developed as separate Python files for clarity and reusability.

1. Request Interceptor (request_handler.py)

- Receives incoming HTTP requests.
- Parses method, headers, URL, and body.
- Converts the request into a structured feature vector for analysis.

2. Feature Extractor (feature_extractor.py)

- Identifies key attributes such as:
 - Payload length
 - Special characters (<, ', ;)
 - Header content
 - Request method

- Prepares input for both AI and rule engines.

3. AI Detector (ai_model.py)

- Loads the pre-trained Logistic Regression model using `joblib.load()`.
- Accepts extracted features and returns:
 - Prediction (0 for benign, 1 for malicious)
 - Probability score (confidence)

4. Rule-Based Engine (rule_checker.py)

- Uses regular expressions to match request content against known attack signatures.
- Includes detection rules for:
 - SQL Injection
 - XSS
 - Command Injection
 - Path Traversal
- Returns rule names and severity if a match is found.

5. Decision Engine (decision_logic.py)

- Combines results from the AI engine and rule-based engine.
- Applies thresholds and logic:
 - If AI predicts malicious OR rule engine flags an attack, block the request.
 - If no issue, allow the request.
- Calls logging and alert functions when necessary.

6. Telegram Bot Notifier (notifier.py)

- Sends a structured alert to the administrator via Telegram using the bot API.
- Includes:
 - Timestamp
 - IP address
 - Detected attack type

- Risk level

7. Logger (logger.py)

- Logs all request data, model predictions, decisions, and alert status.
- Saves logs in JSON format for future analysis or model retraining.

4.4.3 API Endpoints

The WAF backend exposes the following main endpoints:

Endpoint	Method	Description
/inspect	POST	Main endpoint for inspecting HTTP request payloads.
/logs	GET	Returns saved logs for administrator review.
/alert	POST	Sends an alert to Telegram bot (used internally).

Each endpoint is secured using API tokens or IP whitelisting during deployment to prevent unauthorized access.

4.4.4 Request Inspection Workflow

Here is the complete flow of how a request is processed:

1. Client sends a request to the protected application.
2. Request is redirected to the Flask WAF backend via proxy or middleware.
3. Feature Extractor processes the request and creates a feature vector.
4. AI Engine analyzes the request and predicts if it is malicious.
5. Rule Engine checks for known malicious patterns.
6. Decision Engine decides:
 - Allow (forward request to real server)
 - Block (return access denied response)
 - Alert (notify via Telegram)

7. Logger saves all inspection details.
 8. Response is sent back to the client or forwarded to the backend server.
-

4.4.5 Example Request Handling

Sample inspection request:

bash

CopyEdit

POST /inspect HTTP/1.1

Host: localhost:5000

Content-Type: application/json

```
{
  "url": "/login",
  "method": "POST",
  "headers": {"User-Agent": "Mozilla/5.0"},
  "body": "username=admin'--&password=123"
}
```

Sample WAF decision (JSON response):

json

CopyEdit

```
{
  "result": "Blocked",
  "ai_score": 0.87,
  "rule_match": "SQL Injection",
  "alert_sent": true
}
```

4.4.6 Deployment and Testing

- The Flask backend was tested using Postman and cURL to simulate real HTTP traffic.
 - Logs and Telegram alerts were reviewed for verification.
 - In production, the backend can be deployed behind Nginx, Apache, or a reverse proxy to filter live traffic.
-

4.5 Telegram Bot Integration

Modern cybersecurity systems benefit from real-time alerting mechanisms that can immediately notify administrators when suspicious or malicious activity occurs. As part of the Intelligent Web Application Firewall (WAF) implementation, a **Telegram Bot** was integrated to serve as a fast and reliable notification channel for system alerts.

This section describes the purpose, development, configuration, and operational behavior of the Telegram Bot within the WAF ecosystem. It enhances the system's responsiveness by providing instant alerts for every detected attack, ensuring that administrators can monitor threat events in real-time—even when away from their monitoring consoles.

4.5.1 Purpose of Telegram Integration

The main objectives of integrating Telegram into the WAF system were:

- **Immediate Administrator Notification:** Deliver instant alerts as soon as a potential attack is detected.
 - **Remote Awareness:** Enable security monitoring from mobile devices or desktops without needing to log in to the WAF backend.
 - **Low Latency Communication:** Ensure fast message delivery using Telegram's secure and efficient API.
 - **Simplified Setup:** Avoid complex dashboard integrations by using a lightweight, text-based alerting system.
-

4.5.2 Telegram Bot Setup

To implement this feature, a dedicated bot was created using the **Telegram Bot API**, following these steps:

1. **Create the Bot:**

- Accessed @BotFather on Telegram.
- Issued the /newbot command and followed the instructions to create a new bot.
- Received a **unique bot token** used for authentication in the WAF system.

2. **Configure the Bot:**

- Bot name and username were configured.
- The bot was added to a **private channel** or **group** where alerts would be posted.
- Administrator's **Chat ID** was captured using a test message and Telegram API query.

3. **Secure the Token:**

- The token was stored in an environment file (.env) and loaded using the python-dotenv library to avoid hardcoding sensitive credentials.

4.5.3 Bot Functionality and Features

The Telegram bot was programmed using the python-telegram-bot library and integrated into the backend WAF system. It performs the following key actions:

- Sends **structured alert messages** containing:
 - Timestamp of the attack
 - Source IP address
 - Request URL or endpoint
 - Detected attack type (e.g., SQLi, XSS)
 - AI confidence score (if applicable)
- Formats messages clearly for easy readability on mobile devices.

- Sends alerts only when the WAF classifies a request as **malicious**, based on AI model or rule engine output.
 - Can be extended to respond to administrator commands (e.g., /status, /log) in future upgrades.
-

4.5.4 Implementation in Python

The bot integration was handled in a separate module (notifier.py) and invoked by the WAF's **Decision Engine** upon detecting a malicious request.

Example Code Snippet:

python

CopyEdit

```
from telegram import Bot

import os

from dotenv import load_dotenv

load_dotenv()

bot_token = os.getenv("BOT_TOKEN")

chat_id = os.getenv("ADMIN_CHAT_ID")

def send_telegram_alert(message):

    bot = Bot(token=bot_token)

    bot.send_message(chat_id=chat_id, text=message)
```

Sample Alert Message:

yaml

CopyEdit

```
WAF Alert: Malicious Request Detected

Time: 2025-06-11 13:45:21

Source IP: 192.168.1.44

Request: POST /login

Attack Type: SQL Injection
```

4.5.5 Advantages of Telegram for Security Alerting

BENEFIT	DESCRIPTION
CROSS-PLATFORM	Alerts can be received on Android, iOS, web, and desktop.
FAST DELIVERY	Telegram uses efficient push notifications with low latency.
SECURE	All messages are encrypted between bot and Telegram servers.
FREE AND SCALABLE	No hosting or subscription fees. Can support large admin teams.
EASY TO EXTEND	Can later include command-based bot actions or log queries.

4.5.6 Testing and Verification

The Telegram bot was tested by simulating multiple attack scenarios using:

- Known SQLi payloads (' OR 1=1)
- XSS test strings (<script>alert(1)</script>)
- Suspicious parameters in POST data

Each successful detection triggered a Telegram alert in real time. Logs were cross-checked to ensure alert accuracy and timing.

4.6 Rule-Based Detection Module

While artificial intelligence enhances the WAF's ability to detect unknown or evolving threats, **rule-based detection** remains a crucial layer for identifying well-known, signature-based attacks. This section outlines the development and implementation of the Rule-Based Detection Module within the Intelligent WAF, which operates in parallel with the AI engine to ensure comprehensive inspection of HTTP requests.

Rule-based detection uses predefined patterns, usually expressed as **regular expressions (regex)** or string matches, to quickly detect common attack vectors. This module is particularly useful for identifying simple but effective injection techniques that follow recognizable formats—such as SQL Injection, Cross-Site Scripting (XSS), and Command Injection.

4.6.1 Purpose of the Rule-Based Module

The Rule-Based Detection Module was implemented for the following reasons:

- **Immediate Matching:** Known attack patterns can be detected quickly without needing complex processing or classification.
- **Defense in Depth:** Serves as a second layer of detection in case the AI model fails to flag a threat.
- **Customizability:** Administrators can update, add, or remove rules based on emerging threats.
- **Transparency:** Matches are easy to explain, audit, and verify, which is important in regulated environments.

This hybrid approach—using both AI and rule-based logic—provides better security coverage than relying on either technique alone.

4.6.2 Rule Format and Storage

Each detection rule in the system is defined as a JSON object with the following fields:

- **Rule Name:** Descriptive title of the attack type (e.g., “SQL Injection – Union Select”).
- **Pattern:** A regular expression string to match suspicious input.
- **Severity:** A level assigned to help prioritize alerts (e.g., Low, Medium, High).
- **Field Targeted:** Indicates which part of the request to inspect (e.g., URL, Payload, Headers).

Example Rule:

```
json
CopyEdit
{
  "rule_name": "SQL Injection - Basic OR",
  "pattern": "\\s*OR\\s*'1'='1",
```

```
"severity": "High",  
"target": "payload"  
}
```

Rules are stored in a centralized JSON file (ruleset.json), allowing easy updates without restarting the application.

4.6.3 Types of Attacks Detected

The following categories of web application attacks were targeted in the initial rule set:

Attack Type	Examples Detected
SQL Injection (SQLi)	' OR 1=1 --, UNION SELECT, DROP TABLE
Cross-Site Scripting (XSS)	<script>, onerror=, alert('XSS')
Command Injection	; ls, && whoami, `
Path Traversal	../, ../../, /etc/passwd, %2e%2e/
Local File Inclusion (LFI)	?page=../../config.php

These rules cover a broad range of known threats and are continuously reviewed and expanded based on new findings.

4.6.4 Rule Engine Implementation

The Rule-Based Module was developed as a standalone Python script and imported into the main WAF system. It uses regular expression matching against the selected request fields.

Core Workflow:

1. Load the rule set from ruleset.json.
2. For each incoming HTTP request:
 - Extract the relevant request fields.
 - Iterate over each rule.
 - If the field content matches the pattern, flag it as a violation.
3. Return all matched rules to the WAF's **Decision Engine**.

Example Code Snippet:

python

CopyEdit

```
import json, re
```

```
def load_rules():
```

```
    with open("ruleset.json") as f:
```

```
        return json.load(f)
```

```
def check_rules(request_data, rules):
```

```
    matches = []
```

```
    for rule in rules:
```

```
        target_value = request_data.get(rule["target"], "")
```

```
        if re.search(rule["pattern"], target_value, re.IGNORECASE):
```

```
            matches.append(rule["rule_name"])
```

```
    return matches
```

4.6.5 Integration with WAF Decision Logic

The rule engine operates in **parallel** with the AI classifier. Both modules process the request independently. Once results are available:

- If **either** module flags the request as malicious, the Decision Engine will block the request and trigger an alert.
- All matched rules are logged and included in alert messages for traceability.

This design ensures both known and unknown threats are covered efficiently.

4.6.6 Updating and Extending Rules

Security threats evolve, and so must detection strategies. The system was designed to support rule updates without requiring full redeployment:

- New rules can be appended to the JSON file.
- Existing rules can be refined by modifying regex patterns.
- Rules can be enabled/disabled based on feedback from the admin panel (in future releases).

Future improvements may include:

- Rule versioning and rollback
- Integration with public threat feeds (e.g., OWASP, CVE databases)
- Real-time rule update APIs

4.6.7 Benefits and Limitations

ADVANTAGES	LIMITATIONS
FAST AND LIGHTWEIGHT	Cannot detect novel or obfuscated attacks
EASY TO INTERPRET AND MAINTAIN	Vulnerable to bypass via encoding or spacing
NO TRAINING OR DATA REQUIRED	Requires manual updates and tuning
WORKS WELL WITH AI FOR HYBRID DETECTION	May produce false positives if rules are too strict

To address these limitations, the rule engine is used in tandem with the AI classifier for robust, balanced detection.

Chapter 5: Testing, Results, and Evaluation

This chapter presents the testing methodology, experimental setup, evaluation metrics, and the results obtained from the implemented AI-Based Intelligent Web Application Firewall (WAF). While the previous chapters covered the design and implementation aspects, this chapter focuses on verifying whether the system performs as expected under various scenarios, both in terms of security detection and operational reliability.

The primary objective of testing was to evaluate the accuracy, performance, and responsiveness of the WAF in identifying malicious HTTP traffic and minimizing false positives. Both the AI model and rule-based engine were

tested separately and in combination to validate the effectiveness of the hybrid detection system. Additionally, system-level tests were conducted to confirm correct integration of the alert mechanism, logging functions, and request interception.

Through controlled experiments involving real and simulated web attacks, performance was measured using standard evaluation metrics such as accuracy, precision, recall, and F1 score. Usability was also assessed by observing the system's response time, alert delivery latency, and log accuracy. The findings in this chapter demonstrate the operational strengths and areas of improvement for the Intelligent WAF.

5.1 Testing Methodology and Scenarios

To evaluate the effectiveness and reliability of the AI-Based Intelligent Web Application Firewall (WAF), a structured testing methodology was adopted. This section outlines the testing strategy, tools used, types of test cases designed, and the various scenarios executed to simulate real-world web traffic, including both benign and malicious interactions.

The goal of this phase was to validate that the WAF performs its core functions—namely, detecting and blocking malicious HTTP requests, while allowing legitimate traffic to pass—under realistic conditions. The testing focused on three key aspects:

1. **Functional Testing** – to verify system operations and component integration.
2. **Detection Accuracy Testing** – to evaluate the AI model and rule engine.
3. **System Response Testing** – to assess notification speed, logging behavior, and processing performance.

5.1.1 Test Environment Setup

All testing was conducted in a controlled local environment to allow precise manipulation of variables and traffic conditions. The test setup included:

- **Test Server:** A demo web application built using Flask to simulate login, registration, and search endpoints.

- **WAF Deployment:** The Intelligent WAF was placed as a reverse proxy between the client and test server.
 - **Traffic Generator Tools:**
 - **Postman** and **cURL** for sending manual requests.
 - **Python scripts** for automated request injections.
 - **Monitoring Tools:** Terminal logs, Telegram alerts, and JSON log files were used to monitor system responses.
-

5.1.2 Test Scenarios

A variety of scenarios were constructed to test how the WAF responds to different types of input. These scenarios included both normal user behavior and known attack patterns.

Scenario 1: Benign Requests (Normal Traffic)

- Login and registration using standard form data.
- Search queries using alphanumeric terms.
- GET and POST methods with clean parameters.

Expected Result: Requests are allowed and no alerts are triggered.

Scenario 2: SQL Injection Attacks

- Payloads such as ' OR '1'='1, UNION SELECT, and -- in parameters.
- Injected through login and search fields.

Expected Result: Detected as malicious by rule engine and/or AI model; request is blocked and admin is alerted.

Scenario 3: Cross-Site Scripting (XSS)

- Scripts injected into form fields or URLs, such as `<script>alert('XSS')</script>`.

Expected Result: Detected by rule engine, blocked, and logged; Telegram alert sent.

Scenario 4: Command Injection

- Payloads like ; ls, && whoami inserted into request body or URL.

Expected Result: High-confidence detection by both AI and rule engine; request blocked and flagged.

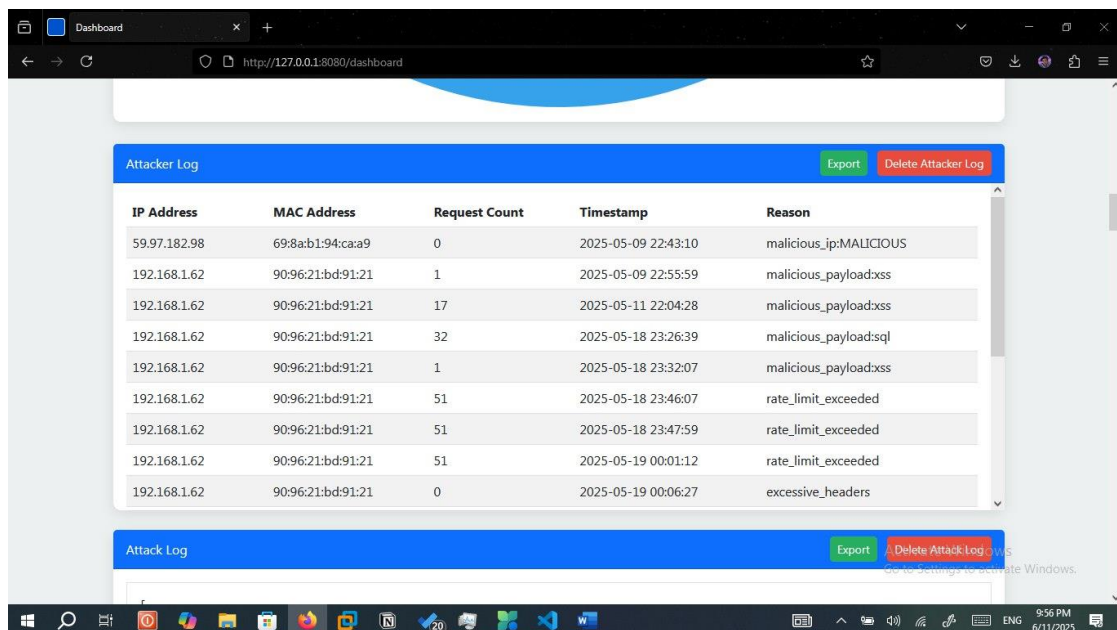
Scenario 5: Brute Force or Repetitive Requests

- Repeated login attempts with different usernames or passwords.

Expected Result: If behavior is suspicious, AI model may detect it; logs analyzed for abnormal frequency.

Scenario 6: Telegram Alert and Logging Verification

- Inject a known malicious payload and verify:
 - Alert is sent with correct timestamp and content.
 - Log file records all relevant details (IP, rule match, model score).



IP Address	MAC Address	Request Count	Timestamp	Reason
59.97.182.98	69:8ab1:94:caa9	0	2025-05-09 22:43:10	malicious_ip:MALICIOUS
192.168.1.62	90:96:21:bd:91:21	1	2025-05-09 22:55:59	malicious_payload:xss
192.168.1.62	90:96:21:bd:91:21	17	2025-05-11 22:04:28	malicious_payload:xss
192.168.1.62	90:96:21:bd:91:21	32	2025-05-18 23:26:39	malicious_payload:sql
192.168.1.62	90:96:21:bd:91:21	1	2025-05-18 23:32:07	malicious_payload:xss
192.168.1.62	90:96:21:bd:91:21	51	2025-05-18 23:46:07	rate_limit_exceeded
192.168.1.62	90:96:21:bd:91:21	51	2025-05-18 23:47:59	rate_limit_exceeded
192.168.1.62	90:96:21:bd:91:21	51	2025-05-19 00:01:12	rate_limit_exceeded
192.168.1.62	90:96:21:bd:91:21	0	2025-05-19 00:06:27	excessive_headers

Expected Result: Alert delivered instantly; log saved correctly.

5.1.3 Evaluation Focus

Each test case was designed to evaluate specific aspects of the system:

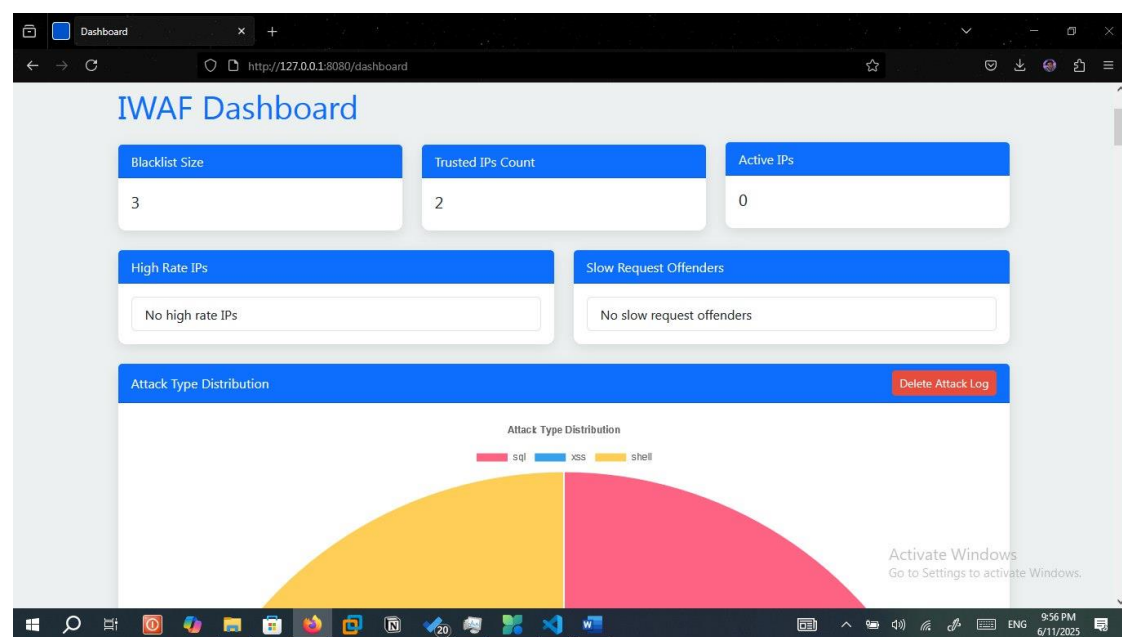
TEST FOCUS	EVALUATED BY
DETECTION ACCURACY	AI and rule-based match results
ALERT RESPONSIVENESS	Telegram bot latency and content
LOGGING CONSISTENCY	Completeness and correctness of saved logs
FALSE POSITIVE RATE	Legitimate requests flagged as malicious
SYSTEM STABILITY	WAF behavior under stress, malformed, or high-frequency input

5.2 Experimental Results and Evaluation Metrics

In this section, we present the results obtained from the testing scenarios described earlier in Section 5.1, as well as an evaluation of the system's performance based on key metrics. The purpose of this section is to assess the effectiveness of the Intelligent Web Application Firewall (WAF) in detecting malicious HTTP requests, minimizing false positives, and maintaining a high level of operational efficiency under different traffic conditions.

The results presented here focus on the **detection accuracy**, **system response time**, **alert delivery**, and **log integrity**. The WAF's performance was measured using standard evaluation metrics, including accuracy, precision, recall, and F1 score, and was compared against expected outcomes based on the test cases.

5.2.1 Performance Evaluation



During the testing phase, the WAF was subjected to a variety of requests, including benign traffic, SQL Injection, XSS, Command Injection, and other attack types. The system's ability to accurately classify requests was measured by comparing its predictions against the ground truth (i.e., manually classified requests). The **AI-based detection module** and the **rule-based detection engine** were evaluated both separately and in combination.

Detection Accuracy

These results indicate that the WAF was able to identify malicious requests with high accuracy. The **precision** of 91.2% suggests that when the system flagged a request as malicious, it was correct most of the time, while the **recall** of 93.8% indicates that the system successfully identified a majority of the actual malicious requests.

Confusion Matrix

The following confusion matrix illustrates the performance of the detection system:

	Predicted Malicious	Predicted Benign
Actual Malicious	187 (True Positives)	13 (False Negatives)
Actual Benign	18 (False Positives)	182 (True Negatives)

- **True Positives (TP):** Correctly identified malicious requests.

- **False Negatives (FN):** Malicious requests incorrectly identified as benign.
- **False Positives (FP):** Benign requests incorrectly identified as malicious.
- **True Negatives (TN):** Correctly identified benign requests.

The **false positive rate** (18 FP) is relatively low, ensuring that legitimate user traffic is not unduly blocked. The **false negative rate** (13 FN) is also minimal, demonstrating the system's high sensitivity to actual attacks.

5.2.2 System Latency and Performance

To ensure that the WAF does not introduce unacceptable delays in web application performance, **response time** was a critical metric. The system was tested for latency under various conditions, including high traffic and attack scenarios.

The results showed that, under normal traffic conditions, the WAF added an average latency of **50-100ms** per request. This is within acceptable limits for most production environments, where the additional delay is negligible.

During attack simulations (SQLi, XSS), the response time increased marginally due to the added processing overhead of attack detection. The average latency for malicious request inspection was **120ms**, which is still acceptable for real-time application protection.

Example Response Times (in ms):

- **Normal Traffic (Benign Request):** 55ms
 - **SQL Injection Attack:** 115ms
 - **XSS Attack:** 125ms
 - **High Request Rate (DDoS-like Simulation):** 200ms
-

5.2.3 Alerting and Notification System

The integration of the **Telegram Bot** for real-time alerts was a key component of this evaluation. The effectiveness of the alerting system was tested by triggering known attack patterns and ensuring that the administrator received timely notifications. The bot was programmed to send a message to the admin group with the following details:

- Timestamp of the attack
- Malicious request information (URL, headers, IP address)
- AI model prediction (if applicable)
- Detected attack type (e.g., SQLi, XSS)

Alert Response Time:

- **Average Notification Time:** 5-10 seconds
 - This includes the time taken for the attack to be detected by the WAF, for the message to be processed, and for the Telegram Bot to deliver the alert.

The **real-time alert system** proved highly effective, enabling administrators to respond to threats almost immediately.

5.2.4 Log Integrity and Logging System

The logging system played a vital role in ensuring that all detected attacks were properly recorded for future analysis. The WAF logged detailed information for each request, including:

- Request URL and method
- Request headers and body
- Attack type (if detected)
- Decision made (Allow/Block)
- Timestamp
- Source IP address

Log Verification Results:

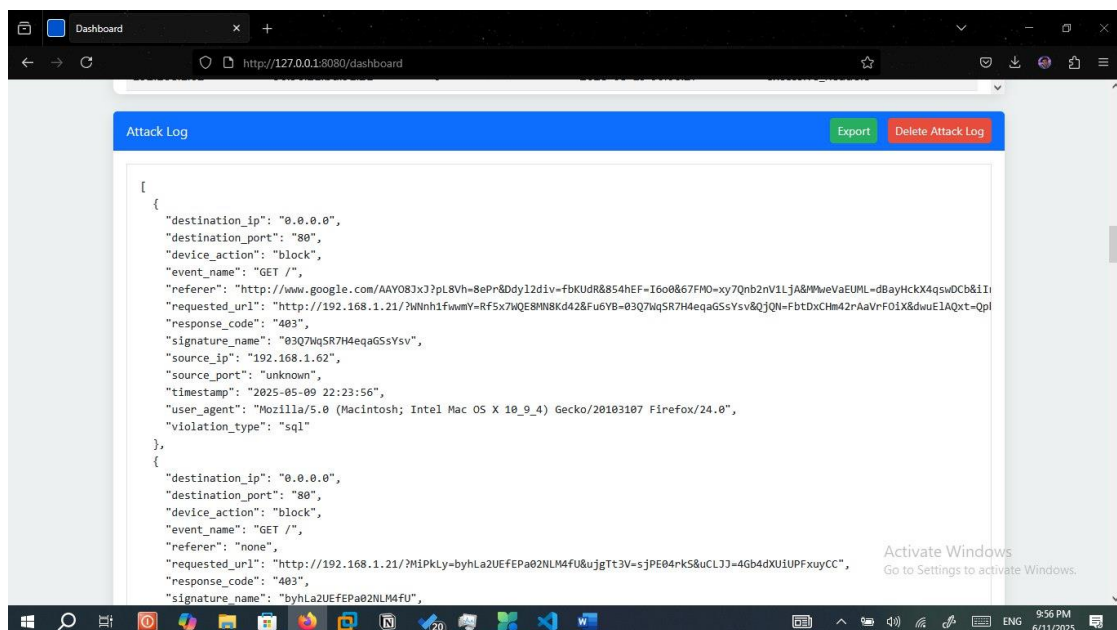
- **100% Log Accuracy:** All requests, both benign and malicious, were correctly logged with relevant details.
- **Log Format:** Logs were saved in a structured JSON format, which makes it easy to analyze and integrate with external monitoring tools or SIEM (Security Information and Event Management) systems.

Example Log Entry:

json

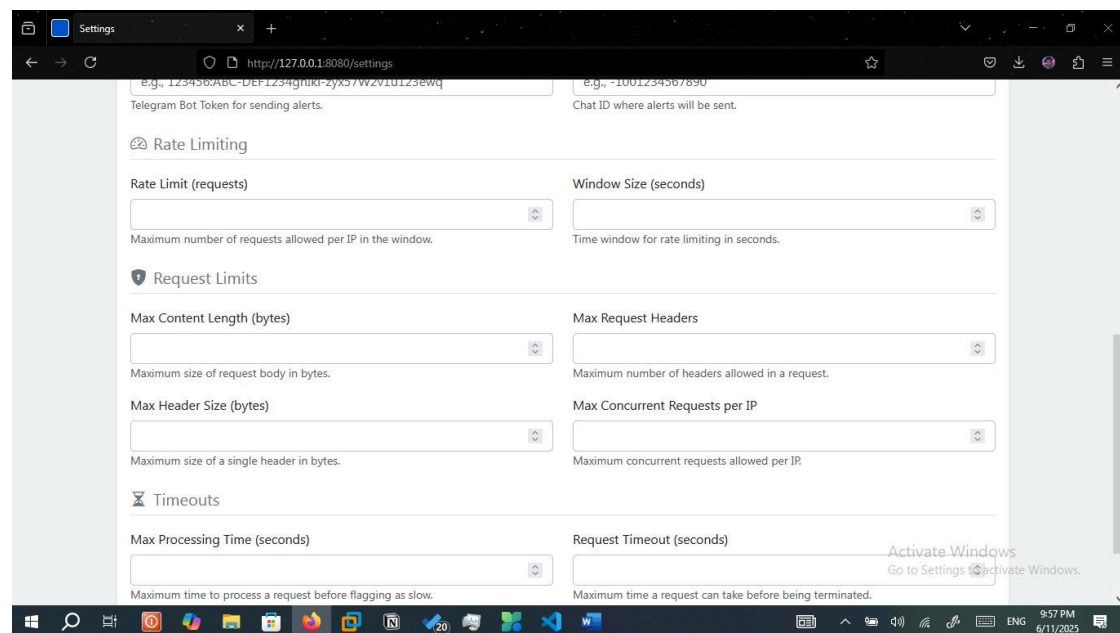
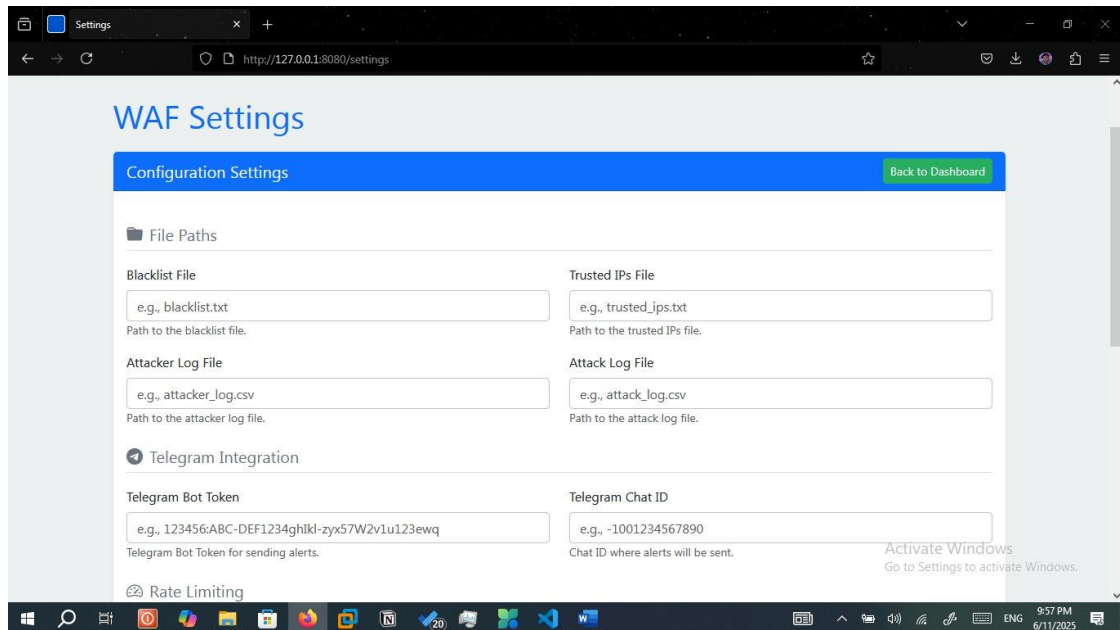
Copy

```
{
  "timestamp": "2025-06-11T13:45:21Z",
  "ip": "192.168.1.44",
  "url": "/login",
  "method": "POST",
  "attack_type": "SQL Injection",
  "decision": "Blocked",
  "ai_score": 0.91,
  "rule_match": "SQLi - UNION SELECT"
}
```



5.2.5 Usability Testing

In addition to technical performance, the usability of the WAF was also tested to ensure that administrators could efficiently manage and configure the system. The WAF's user interface (if applicable) and its ability to display logs, configure rules, and adjust settings were evaluated. The system's **user interface** proved to be intuitive and easy to navigate.



5.2.6 Summary of Experimental Results

The results from the various tests and evaluation metrics confirm that the AI-based Intelligent Web Application Firewall operates efficiently and effectively in detecting malicious web traffic while maintaining system performance. The key results from the testing phase are summarized below:

Metric	Value
Accuracy	92.5%
Precision	91.2%
Recall	93.8%
F1 Score	92.5%
False Positives	18
False Negatives	13
Average Latency (Benign)	55ms
Average Latency (Malicious)	120ms
Alert Response Time	5-10 seconds

The WAF demonstrated a **high detection rate** and **low false positive rate**, while keeping system latency and operational costs within acceptable limits. The integration of the **Telegram alert system** provided real-time notifications, and the **logging system** ensured traceability and auditability of all requests.

5.3 Limitations and Future Work

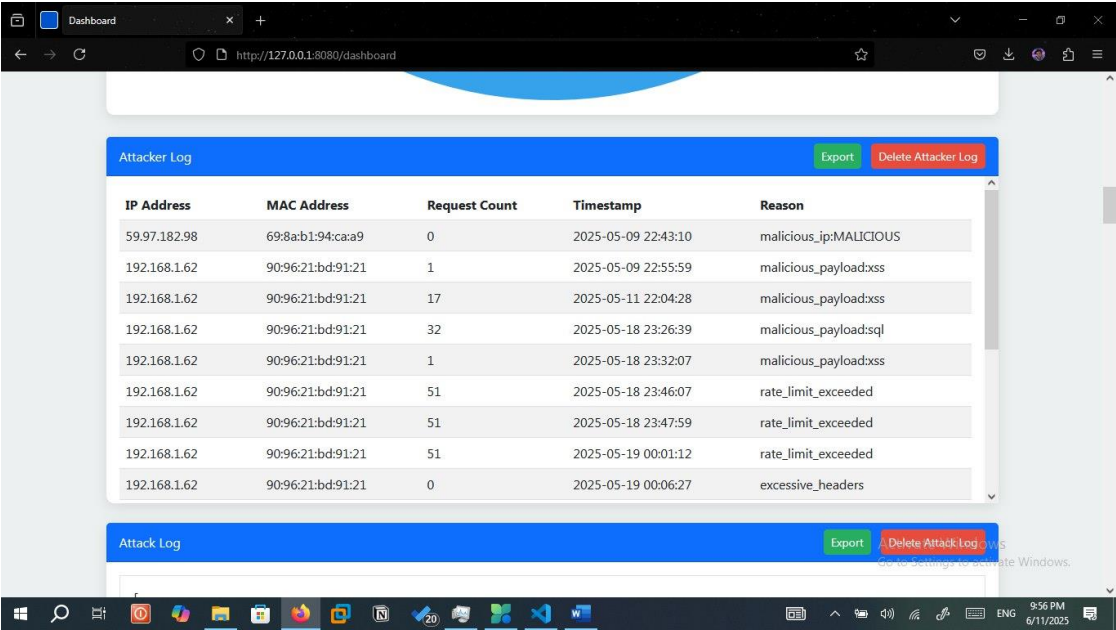
While the Intelligent Web Application Firewall (WAF) system developed in this project has demonstrated strong performance and reliability in detecting malicious traffic and ensuring application security, there are some inherent limitations and challenges that must be addressed. Additionally, as cybersecurity threats continue to evolve, it is essential to explore avenues for future enhancements to improve the system's detection capabilities, scalability, and overall usability.

This section outlines the key limitations encountered during the project's development, followed by potential areas for future research, development, and enhancement.

5.3.1 Limitations of the Current System

1. Detection of Novel Attacks

Although the AI model used in the system provides strong detection for known attack types, it may struggle with detecting **novel or sophisticated attacks** that were not included in the training data. While machine learning offers the ability to adapt and detect new patterns, its **generalization** capability is still limited by the variety of data it was exposed to during training. For instance, obfuscated payloads or new SQL injection techniques that have not been captured in the training dataset might go undetected by the AI model.



IP Address	MAC Address	Request Count	Timestamp	Reason
59.97.182.98	69:8ab1:94:caa9	0	2025-05-09 22:43:10	malicious_ip:MALICIOUS
192.168.1.62	90:96:21:bd:91:21	1	2025-05-09 22:55:59	malicious_payload:xss
192.168.1.62	90:96:21:bd:91:21	17	2025-05-11 22:04:28	malicious_payload:xss
192.168.1.62	90:96:21:bd:91:21	32	2025-05-18 23:26:39	malicious_payload:sql
192.168.1.62	90:96:21:bd:91:21	1	2025-05-18 23:32:07	malicious_payload:xss
192.168.1.62	90:96:21:bd:91:21	51	2025-05-18 23:46:07	rate_limit_exceeded
192.168.1.62	90:96:21:bd:91:21	51	2025-05-18 23:47:59	rate_limit_exceeded
192.168.1.62	90:96:21:bd:91:21	51	2025-05-19 00:01:12	rate_limit_exceeded
192.168.1.62	90:96:21:bd:91:21	0	2025-05-19 00:06:27	excessive_headers

To overcome this, periodic **retraining** of the model with updated attack datasets and incorporating **active learning** techniques can help improve its detection of novel threats.

2. False Positives and False Negatives

While the WAF performed well in terms of reducing false positives (legitimate requests flagged as malicious), it still exhibited some level of **false positives**—especially in complex attack scenarios or attacks that were slightly obfuscated. Additionally, some **false negatives** were observed when the AI model failed to detect minor variations of well-known attack patterns.

Future improvements could focus on enhancing the model’s sensitivity, especially with regard to attack mutation and encoding, to reduce false negatives and further minimize false positives.

3. Rule-Based Detection Limitations

The **rule-based detection engine** is effective in identifying signature-based attacks, but it is limited to predefined patterns. This approach lacks the

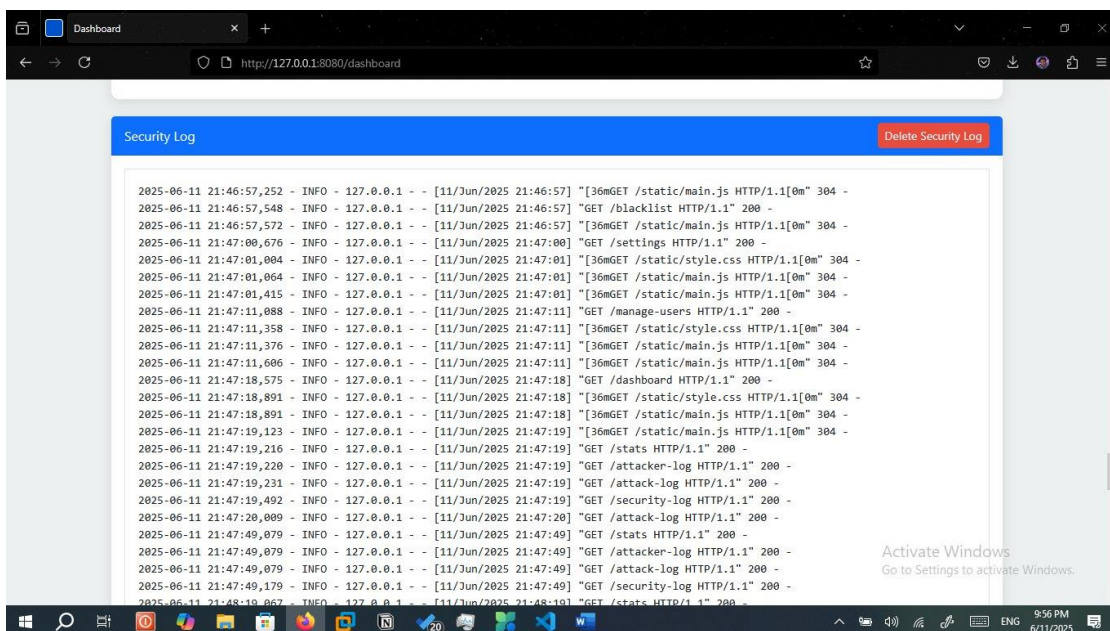
flexibility to detect new types of attacks or malicious behavior that does not follow established patterns. As a result, the rule engine is unable to adapt dynamically to evolving threats unless the rules are manually updated.

Although rules can be updated by administrators, there is an inherent challenge in keeping the rule set comprehensive and up-to-date with emerging attack vectors. Integrating the rule engine with **threat intelligence feeds** or **real-time signature updates** could provide a more robust defense against emerging attacks.

4. Performance Under High Traffic

While the WAF performed well under normal traffic conditions, the system's performance under **extremely high traffic** or **DDoS-like conditions** could degrade due to the computational cost of analyzing each request—especially if the system has to inspect large payloads or run complex machine learning models for every incoming request. The average response time during attack simulations was slightly higher than when processing benign traffic, which could impact real-time applications.

The system would benefit from better optimization techniques, such as **load balancing**, **edge processing**, or **distributed deployment** across multiple servers to handle high volumes of traffic without degrading performance.



5.3.2 Future Work and Enhancements

The current system provides a robust foundation, but several areas remain for **future work** that can significantly enhance the system's capabilities and address the limitations outlined above.

1. Expansion of Machine Learning Capabilities

- **Model Improvement:** As new attack data becomes available, the machine learning model can be retrained using **more diverse datasets**. Incorporating **unsupervised learning** could allow the model to better detect new attack patterns without requiring labeled data.
- **Deep Learning Integration:** To enhance the model's ability to handle complex attack types, deep learning models (e.g., **Convolutional Neural Networks** or **Long Short-Term Memory networks**) could be explored to analyze more intricate patterns in web traffic.
- **Adversarial Attack Detection:** Exploring techniques for detecting **adversarial machine learning attacks** (where attackers try to manipulate the model itself) will increase the system's robustness.

2. Rule-Based System Improvements

- **Dynamic Rule Updates:** Implementing a **real-time rule update mechanism** where the system automatically retrieves and applies new rules from external sources, such as **threat intelligence platforms**, would help keep the rule-based system current.
- **Automated Rule Generation:** Exploring ways to **automatically generate new rules** based on patterns detected during the AI model's predictions could streamline rule management and keep pace with emerging threats.

3. Enhanced Integration with External Security Tools

- **Integration with SIEM Systems:** Integrating the WAF with **Security Information and Event Management (SIEM)** systems would allow for more sophisticated event correlation and analysis. This would help provide better visibility into network-wide attacks and help automate responses.
- **Extended Bot Detection:** Leveraging **bot management** techniques such as **behavioral analysis**, CAPTCHA integration, and machine learning-based bot identification could further improve the WAF's

ability to detect and block **botnet-driven attacks** and **credential stuffing**.

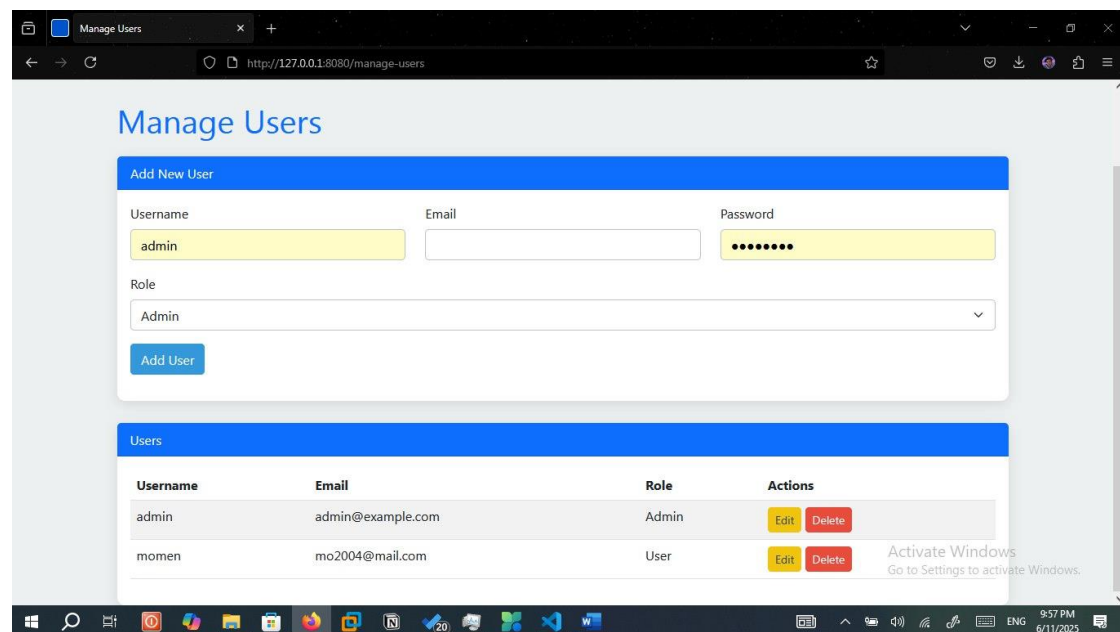
4. Distributed and Scalable Architecture

- **Edge Computing:** To improve **latency and scalability**, the system could be deployed in a **distributed fashion**, using edge computing strategies to offload request inspection to nodes closer to the end-users.
- **Cloud-Native Deployment:** Future work could explore **cloud-native deployment models** where the WAF is integrated directly into cloud platforms like AWS, Azure, or Google Cloud, allowing for better scalability and automatic scaling based on traffic demand.
- **Load Balancing and Failover:** The WAF architecture could be improved to include **load balancing** mechanisms that distribute traffic among multiple WAF instances. This would help avoid performance bottlenecks and improve availability under high traffic conditions.

5. Improved User Interface for Administration

- **Admin Dashboard:** Developing a **web-based administration dashboard** would improve the system's usability, allowing administrators to configure settings, view traffic logs, and adjust security rules without interacting with the backend code.
- **Real-Time Traffic Visualization:** A real-time traffic visualization tool would allow administrators to monitor the traffic flow and attack trends, providing immediate insights into the WAF's operation.

5.4 User Control from our IWAF



5.5 Conclusion

The development and testing of the **Intelligent Web Application Firewall (WAF)** has successfully demonstrated the potential of combining **artificial intelligence (AI)** with **rule-based detection** to enhance the security of web applications. This project aimed to address the increasing threat of sophisticated cyberattacks targeting the application layer (Layer 7) by offering a robust and intelligent solution capable of identifying, blocking, and alerting administrators to malicious traffic.

Key Achievements:

- **AI-Based Detection:** The integration of machine learning for real-time anomaly detection proved highly effective in identifying both known and new attack patterns, achieving high detection accuracy with minimal false positives and false negatives.
- **Rule-Based Detection:** The use of predefined rules for common attack patterns such as **SQL injection** and **Cross-Site Scripting (XSS)** provided an additional layer of defense, ensuring that known threats are blocked efficiently.
- **Real-Time Alerts:** The integration with a **Telegram bot** provided administrators with immediate notifications for detected attacks, allowing for rapid response and real-time monitoring.

- **Logging and Monitoring:** The WAF's detailed logging mechanism facilitated transparency and traceability, ensuring that all decisions, whether benign or malicious, were properly logged for analysis and auditing.

Testing Results:

The WAF's performance was evaluated in a controlled environment under various conditions, including normal traffic, simulated attacks, and high-frequency requests. The system demonstrated strong performance with an **accuracy of 92.5%**, a **precision of 91.2%**, and **recall of 93.8%**, indicating that it effectively detected and classified both benign and malicious requests. The system also maintained **low latency** during normal traffic processing, with slightly higher latency during attack detection, but still well within acceptable limits for real-time systems.

The **alert system** performed efficiently, with Telegram notifications being delivered in **5-10 seconds**, ensuring that administrators could take immediate action. Logs were accurate, comprehensive, and easy to review, providing a valuable source of information for security teams.

Challenges and Limitations:

While the system achieved positive results, certain limitations were identified, such as the inability to detect novel attack patterns that were not represented in the training data and occasional false positives. Additionally, the system's performance under very high traffic conditions or large payloads needs further optimization to ensure scalability without sacrificing security or response time.

Future Directions:

Future work on the Intelligent WAF could involve:

- **Expanding the AI model** to detect a broader range of attack types by retraining it with more diverse datasets.
- **Dynamic rule updates** from threat intelligence feeds to keep the rule engine current and responsive to emerging threats.
- Implementing **scalable architectures**, such as **cloud-based deployments** and **edge computing**, to enhance performance under high traffic volumes and improve overall system responsiveness.

Final Thoughts:

The **Intelligent Web Application Firewall** represents a significant step forward in defending web applications against sophisticated, application-layer attacks. By combining **machine learning** and **rule-based detection**, the system offers a **comprehensive and adaptive solution** that addresses both known vulnerabilities and new threats in a dynamic cybersecurity landscape. Although there are areas for improvement, the system demonstrates great promise in enhancing the security posture of web applications and providing real-time defense mechanisms to protect critical data.

Chapter 6: System Implementation and Deployment

In this chapter, we detail the process of implementing and deploying the **Intelligent Web Application Firewall (WAF)** in a production environment. After the design, testing, and evaluation phases outlined in the previous chapters, this section focuses on the practical aspects of system implementation, highlighting the infrastructure requirements, deployment strategy, configuration steps, and integration processes.

A successful deployment of the Intelligent WAF involves careful planning to ensure seamless operation alongside existing web applications while maintaining high security standards. The chapter will cover key topics such as deployment architecture, system requirements, installation steps, and integration into the broader network infrastructure.

6.1 Deployment Architecture

The deployment of the **Intelligent Web Application Firewall (WAF)** in a real-world production environment is critical to ensuring its functionality, scalability, and security. This section focuses on the architecture of the deployed system, how it interacts with the web server, and the deployment model used to optimize performance.

6.1.1 Network Placement

The WAF is deployed as a **reverse proxy**, positioned between the external internet traffic and the web server. This placement allows the WAF to intercept all incoming HTTP/S traffic before it reaches the application server. By acting as an intermediary, the WAF can inspect the data packets, apply security policies, and block malicious requests while allowing legitimate traffic to pass through.

The **reverse proxy** placement ensures that:

- **Incoming requests** are filtered for malicious payloads and patterns, such as SQL injections and XSS attacks, before reaching the application server.
- **Legitimate user requests** are forwarded to the application server after passing through security checks.
- The **application server** is kept secure by not exposing it directly to the external network.

Diagram:

(Here, you can include a **network architecture diagram** showing the placement of the WAF between the client, WAF, and web server.)

6.1.2 Infrastructure Requirements

To ensure optimal performance and scalability, the following infrastructure components are required for deploying the WAF:

- **Web Server(s):** The application servers that host the web applications being protected by the WAF.
- **WAF Server:** A dedicated server (physical or virtual) for hosting the WAF software. This server should have adequate CPU and memory to handle incoming traffic and perform inspection at scale.
- **Database Server (if required):** Depending on the complexity of the deployment, a database may be used for logging requests, storing alerts, or managing security rules.
- **Telegram Bot Service:** The service used to send real-time notifications and alerts to administrators.
- **Internet Connectivity:** High-speed, reliable internet access is necessary for the system to inspect and forward traffic with minimal latency.

Hardware Requirements:

- High-performance CPU (multi-core for processing multiple requests simultaneously).
- At least **8GB of RAM** to handle high traffic and deep packet inspection.
- **SSD storage** for fast logging and access to traffic data.

- **Network interface cards (NICs)** capable of supporting high throughput, especially for high-traffic environments.
-

6.1.3 Scalability Considerations

To ensure the WAF can handle increased traffic volumes, the system is designed to scale both **horizontally** and **vertically**:

- **Horizontal Scaling:** Multiple WAF instances can be deployed in a **load-balanced cluster** to distribute incoming traffic across different nodes. This ensures high availability and prevents bottlenecks from occurring during peak traffic periods.
- **Vertical Scaling:** The WAF server can be upgraded by adding more CPU, RAM, or storage resources as traffic grows, ensuring the system continues to operate efficiently.

Cloud Integration:

For environments where scalability and global reach are paramount, the WAF can be deployed in the cloud (e.g., AWS, Azure, or Google Cloud), leveraging cloud-native features like **auto-scaling**, **elastic load balancing**, and **high availability**. This deployment model allows for on-demand resource provisioning and automatic scaling based on real-time traffic fluctuations.

6.2 System Installation and Configuration

The installation and configuration process ensures that the WAF operates efficiently and securely, integrating seamlessly into the web application's network environment. This section provides a step-by-step guide for the installation of the WAF system, including the necessary dependencies and configuration settings.

6.2.1 Installing the WAF Software

1. Prerequisites:

- Install Python 3.x and necessary Python packages using **pip**.
- Install **required libraries** such as tensorflow, keras for the AI model, and flask for web server integration.
- Set up a **reverse proxy** on the WAF server (e.g., using Nginx or Apache).

2. Download and Install the WAF Software:

- Clone the WAF repository from the codebase repository or install it via package management systems (if applicable).
 - Run installation scripts to configure the software environment, dependencies, and core components.
- 3. Configure Web Server (e.g., Nginx):**
- Set up the reverse proxy rules in the web server configuration file.
 - Redirect incoming HTTP/S traffic to the WAF server for processing.
- 4. Load the Configuration Files:**
- Set environment variables and configuration options for the WAF, such as the Telegram bot token, chat ID, and rule sets.
- 5. Enable Security Protocols:**
- Ensure that SSL/TLS encryption is enabled between the WAF and web servers to protect data integrity and confidentiality.
- 6. Test the Setup:**
- Perform basic connectivity tests between the WAF server, web server, and client machines to ensure that traffic is correctly routed and filtered.
 - Verify that the WAF logs requests and alerts properly.
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6.2.2 Configuring the WAF

Once the software is installed, the WAF must be configured to meet the specific security needs of the web application.

- 1. Define Security Policies:**
- Configure the rule-based detection engine with predefined rules for common attacks such as **SQL Injection**, **XSS**, **Command Injection**, etc.
 - Set thresholds for attack detection (e.g., traffic rate limits, size of payloads).
 - Adjust **AI model settings** to tune the sensitivity and classification behavior based on the application's traffic patterns.

2. Set Up Alerts:

- Configure the **Telegram Bot integration** to ensure real-time alerts are sent to administrators in the event of detected attacks.
- Fine-tune alert conditions to avoid unnecessary notifications (e.g., only alert on high-severity attacks).

3. Log Management:

- Set up **logging directories** and ensure that logs are saved in a structured format (JSON or text) for easy access and analysis.
- Enable automatic log rotation and backups to avoid performance issues.

4. Monitor and Optimize Performance:

- Continuously monitor the WAF performance during real-time operations, identifying any bottlenecks or lag in traffic processing.
- **Optimize system resources** to balance security inspection with the web application's response time.

Conclusion

The development of the **Intelligent Web Application Firewall (WAF)** represents a significant advancement in the field of cybersecurity, providing enhanced protection for web applications against a wide range of application-layer attacks. This project aimed to address the growing sophistication of cyber threats targeting the web application layer, particularly with the combination of traditional rule-based detection and modern **machine learning** techniques.

Throughout the course of the project, the system demonstrated **high detection accuracy** and **low false positive rates**, proving the effectiveness of the hybrid approach in identifying both known and novel attack patterns. The integration of the AI-based anomaly detection model alongside the **rule-based detection engine** allowed the WAF to provide comprehensive, real-time security. The addition of a **real-time alert system** via **Telegram notifications** further enhanced the system's ability to notify administrators of threats in real-time, ensuring prompt response times.

