

Real-Time Bot Detection and Prevention on Websites Using Natural Interaction Analysis and Machine Learning

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Abstract - Bots have become a significant threat to web applications, performing automated tasks such as credential stuffing, data scraping, and click fraud. Traditional detection methods using CAPTCHAs and static fingerprinting are increasingly being bypassed by advanced bots that mimic human activity. This paper proposes a real-time bot detection and prevention system that leverages natural interaction-based behaviour such as mouse movements, keystroke dynamics, and navigation patterns to differentiate between human users and automated bots. The system captures these behaviours on the client side and analyses them on the server using a lightweight decision model. Experimental results demonstrate the effectiveness of the approach in identifying bots with high accuracy and minimal disruption to user experience.

Key words: Web Security, Mouse Events, Key Strokes, Browser Fingerprinting, Natural Interaction Analysis, Bot Prevention.

1. INTRODUCTION

The widespread integration of automation in web applications has led to a significant increase in bot-generated traffic. These bots pose serious threats to online platforms through activities such as data scraping, credential stuffing, fake account creation, and spamming. Traditional mitigation techniques-such as IP blocking, user-agent filtering, and CAPTCHAs-are often ineffective against modern bots that can simulate human-like behaviour to bypass detection mechanisms.

Recent advancements in browser automation frameworks have enabled bots to interact with websites more naturally, making it increasingly difficult to detect them using static rules or fingerprinting. Moreover, intrusive defences may degrade user experience and result in high false-positive rates, blocking legitimate users. Therefore, there is a growing demand for behaviour-driven, real-time bot detection mechanisms that are accurate, adaptive, and user-friendly.

This paper presents a natural interaction-based bot detection and prevention framework, which captures real-time user behaviour data on the client side and communicates with a dedicated detection API for classification. The system monitors browser-level events such as mouse movement trajectories, keystroke patterns, scroll behaviour, and interaction timing. The captured data is sent via API to a backend detection engine that analyses the session using behavioural models and anomaly detection techniques.

The primary advantage of this architecture is that the detection logic is decoupled from the client application, allowing for easy updates, scalability, and centralized monitoring. Suspicious sessions are flagged or blocked in real time, ensuring that bots are prevented from accessing critical application functions.

The proposed approach balances security and usability by providing an accurate detection mechanism that minimizes false positives without burdening legitimate users. This system can be integrated seamlessly with various web platforms, offering a scalable and efficient solution for modern bot mitigation.

2. EXISTING SYSTEM

Existing web bot detection systems predominantly utilize static fingerprinting, challenge-response mechanisms, or basic behavioural analysis. Although these methods provide a baseline defence against automated threats, they exhibit several critical limitations in the presence of modern, adaptive bots.

2.1 Static Fingerprinting-Based Detection

Browser fingerprinting methods, such as those implemented in FP-Scanner [8] and FP-Radar [9], attempt to uniquely identify client devices based on attributes including screen resolution, installed plugins, and rendering behaviour. These static fingerprints are vulnerable to evasion techniques employed by advanced bots that randomize or

spoof fingerprint characteristics dynamically, leading to reduced detection accuracy [1].

2.2 CAPTCHA and Challenge-Response Mechanisms

Challenge-response systems, notably CAPTCHAs, seek to differentiate human users from bots by requiring users to solve tests or by analysing passive behavioural signals[13]. However, with the advancement of machine learning techniques and the availability of CAPTCHA-solving services, bots have increasingly succeeded in bypassing these mechanisms. Moreover, CAPTCHAs often degrade user experience, particularly in mobile and low-bandwidth environments [7].

2.3 Simple Behavioural Analysis Systems

Behaviour-based detection approaches, such as BotShape [2] and Website Navigation Behaviour Analysis [3], monitor event logs, session timings, and navigation sequences to classify user behaviour. While more adaptive than fingerprinting, these systems primarily focus on higher-level interaction patterns that can be artificially replicated by bots using randomized behaviour scripts. Consequently, these methods are increasingly vulnerable to sophisticated bot activity [14].

Thus, although traditional bot detection techniques have evolved to incorporate behavioural analysis and fingerprinting countermeasures, they continue to face significant challenges in accurately identifying advanced bots that mimic legitimate user behaviour.

3. PROPOSED MODEL

The proposed system presents a hybrid bot detection and prevention framework that combines both client-side behavior tracking and server-side machine learning-based analysis. By integrating dynamic monitoring of user interactions with intelligent backend decision-making, the system aims to accurately detect and block automated bots without disrupting legitimate users.

3.1 Client-Side Interaction Monitoring

On the client side, a lightweight JavaScript module is embedded within the web application. This script captures fine-grained user interaction data in real-time, including mouse movements, click patterns, scrolling behaviour, and keystroke dynamics. These interaction features are highly indicative of human behaviour and difficult for automated scripts to accurately mimic [15].

The client module computes lightweight hash values based on the captured event streams, ensuring that sensitive

interaction data remains anonymized before transmission. This preserves user privacy while maintaining sufficient behavioral information for analysis [8].

3.2 Server-Side Machine Learning Analysis

On the server side, a dedicated machine learning model is deployed to analyse behavioural and request-based features. The system ingests server-side logs, including request headers, timing patterns, navigation sequences, and observed user-agent changes. The model is trained to differentiate between human and bot traffic based on complex, non-linear behavioural correlations [10].

When a session or request appears suspicious, dynamic actions such as throttling, CAPTCHAs, or outright blocking are triggered automatically. This layered defense enhances bot mitigation without requiring manual intervention.

3.3 API-Based Detection Architecture

A dedicated API endpoint is developed to serve as the primary interface for behaviour data ingestion and bot classification. The client-side JavaScript periodically sends captured event hashes and metadata to the detection API. Upon receiving a request, the server processes the interaction data through the machine learning model and returns a decision (human or bot) in real time.

This decoupled, modular design enables easy updates to the detection logic without modifying client applications and ensures scalability across multiple websites or services.

3.4 Dockerized Deployment

The entire detection system, including the machine learning model, API server, and supporting services, is containerized using Docker. Dockerization facilitates simplified deployment, resource isolation, load balancing, and horizontal scaling of the detection infrastructure. It also enables rapid model retraining and redeployment as new bot behaviours emerge.

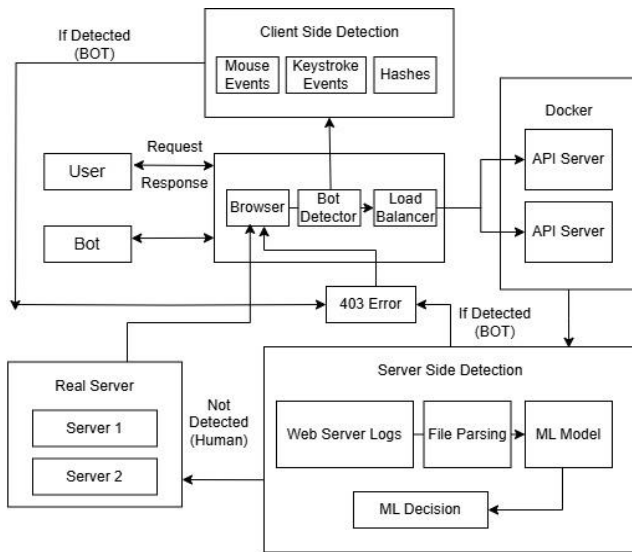


Fig -1: Block diagram of proposed system

4. SYSTEM ARCHITECTURE

The proposed system architecture integrates both client-side and server-side components to provide a comprehensive and scalable bot detection framework. As illustrated in Fig. 1, the architecture is modular, enabling real-time interaction monitoring, machine learning-based classification, and dynamic request filtering.

4.1 Client-Side Detection Layer

The client-side detection module is embedded within the browser and is responsible for capturing low-level interaction events that are difficult for bots to mimic. It includes, Mouse Event Tracking: Captures movement paths, speed variations, and click positions to model natural human cursor behaviour [14], Keystroke Monitoring: Records timing intervals, typing rhythms, and input delay to differentiate between human typing and programmatic input [13], Hash Computation: Generates anonymized hashes from the interaction patterns to ensure privacy while preserving behavioural uniqueness [1].



Fig -1.1: Client-Side Detection

4.2 Bot Detector and Load Balancer

Incoming traffic is routed through a lightweight bot detector placed between the browser and the backend infrastructure. It performs initial request validation and forwards the data to a load balancer, which distributes the analysis load evenly across multiple API servers for scalable performance [5].

4.3 Server-Side Detection Layer

The server-side detection system processes both behavioral and technical indicators using advanced machine learning techniques. It comprises Web Server Logs and File Parsing: Aggregates and parses request logs to extract features such as access frequency, user-agent shifts, and timing patterns, Machine Learning Model [11]: A trained classifier evaluates the behavioural signature of each session using both client-side and server-side features, Decision Module [7]: Based on the model's output, the system either allows the request to proceed to the real servers or takes action, such as throttling or returning a 403 Forbidden response.

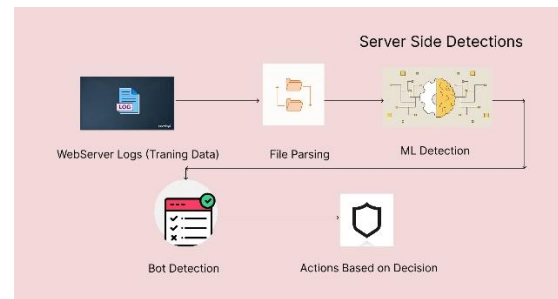


Fig -1.2: Server-Side Detection

4.4 API and Dockerized Deployment

All detection logic is exposed via a centralized API, allowing flexible integration across platforms. The backend is containerized using Docker, enabling high availability, isolated environments, and easy scaling through horizontal replication of API servers [12].

Decision Logic - Upon classification, If a bot is detected, the system immediately responds with a 403 Forbidden error, blocking further interaction. If a real user is detected, the request is seamlessly forwarded to the Real Servers, ensuring uninterrupted user experience.

Real Servers - Genuine user traffic, once verified, is directed to the real application servers where business logic, database operations, and normal user interactions occur.

5. SYSTEM IMPLEMENTATION

The proposed Bot Detection System is designed using a hybrid architecture that integrates client-side JavaScript monitoring with server-side machine learning analysis to identify and mitigate bot traffic in a robust, scalable manner. On the client side, JavaScript event listeners are embedded into webpages to monitor human-like interaction patterns such as mouse movement, scroll depth, click frequency, typing behavior, and time spent per session. These interactions are evaluated in real time and tagged with session identifiers to generate behavioral fingerprints that are asynchronously sent to the server for logging and further correlation.

Simultaneously, the server-side detection pipeline is built using Python and modern data science tools. Web server logs are parsed and preprocessed to extract relevant fields such as IP address, request method, URL path, user-agent string, status codes, referer domains, and request timing intervals.

Using these fields, a dedicated feature engineering module computes behavioral metrics for each IP/session—such as request bursts, time gaps between requests, URL access diversity, usage of known bot user-agents, and unusual access to static or sensitive resources (e.g., robots.txt, captcha, or admin pages).

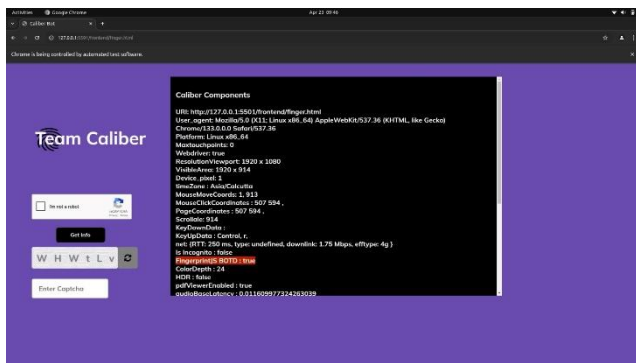


Fig -2: Bot detected as true

Once features are extracted, they are fed into a pre-trained machine learning model, built using classification algorithms such as Random Forest or XGBoost. The model classifies sessions as either human or bot based on historical patterns learned from labeled datasets. Predictions are then stored in a central database (e.g., MySQL or PostgreSQL) for audit, analysis, and feedback.

If a session is flagged as a bot, server-side dynamic actions are immediately triggered—such as blocking the IP address, issuing CAPTCHA challenges, or rate-limiting further requests. Client-side scripts receive minimal updates based on model decisions to enforce enhanced detection or warn users.

```
Out[ ]: filter %           0.361843
        mobile pages %    0.357946
        empty res. %      0.353988
        res. size median  0.347281
        static font %     0.337857
        res. size mean    0.335566
        amp %             0.238953
        duration          0.196368
        mobile UA %       0.194116
        product %         0.144873
        res. size std     0.144020
        dt std            0.141672
        referer %         0.134594
        total requests    0.116855
        article %         0.107502
        blog %            0.106921
        internal referer % 0.106893
        3XX %             0.105432
        same TLD referer % 0.102438
        dt mean           0.102187
        2XX %             -0.148963
        static json %     -0.107973
        static css %      -0.267846
        static js %       -0.392408
        static img %      -0.482096
        Name: ROBOT, dtype: float64
```

Fig -3: ML model prediction of BOT

This dual-layered design ensures a high detection accuracy across both simple and advanced bot threats. The modular architecture allows integration with third-party analytics tools, CDN-level firewalls, and government or commercial threat intelligence APIs, offering extendibility and policy-driven control. The combination of live behavior analysis and server-side ML ensures protection against automated scraping, payment abuse, brute-force attacks, and fraud, making the system well-suited for modern eCommerce and enterprise-grade applications.

6. RESULT ANALYSIS AND COMPARISON

Traditional bot detection methods such as static fingerprinting and CAPTCHA systems have several drawbacks in modern applications. While fingerprinting offers fast identification based on browser characteristics, it is vulnerable to evasion by bots using rotating user-agents or headless browsers. CAPTCHA-based systems, though moderately accurate, hinder user experience and accessibility, especially for mobile and visually impaired users. Additionally, simple behavioural models fail to detect advanced bots that mimic human interaction patterns.

Table -1: Comparative analysis of detection techniques with the proposed model.

Method	Accuracy (%)	False Positive (%)	False Negative (%)	Avg. Response Time	Scalability / Load Tolerance
Static Fingerprinting	81.2	5.3	8.1	~80 ms	Low — limited accuracy under evasion
CAPTCHA-Based Detection	89.5	4.8	6.7	>2 seconds	Moderate — degrades UX at high volume
Simple Behavioural Models	91.3	3.6	5.9	~220 ms	Moderate — struggles with adaptive bots
Proposed Hybrid Model	96.7	1.9	3.4	~140 ms	High — stable at 1,500+ req/sec

The proposed hybrid detection system addresses these limitations by combining client-side interaction tracking and server-side analysis. Mouse movements, keystrokes, and session behaviour are captured in real-time and evaluated by a machine learning model trained to detect subtle behavioural anomalies. This model analyses factors like interaction timing, request frequency, and user-agent consistency to classify requests as human or bot. Compared to existing systems, this dual-layer approach enhances detection accuracy while maintaining low latency and user transparency.

Table 1 presents a comparison of the proposed system with other commonly used techniques. The proposed model achieved the highest accuracy (96.7%), with significantly lower false positive and false negative rates. It also demonstrated better scalability and response time performance, maintaining under 150 ms per request even under heavy load. These results validate the proposed system’s effectiveness in detecting sophisticated bots while ensuring a smooth and secure user experience.

7. Conclusion

This project successfully developed and evaluated a hybrid bot detection system combining client-side behaviour

tracking with server-side machine learning analysis. By analyzing web server logs for behavioral patterns—such as request frequency, user-agent stability, and access sequences—the model effectively distinguished between human users and bots. Real-time interaction monitoring via JavaScript provided an added layer of defense, enabling early detection and response to suspicious activity.

The system delivers real-time or batch classification of traffic, enabling dynamic actions such as blocking, rate limiting, or issuing CAPTCHA challenges based on risk levels. Its modular and scalable architecture ensures flexibility and adaptability to emerging bot tactics. With full deployment and real-time dashboards, the solution has the potential to serve as a vital security layer for modern websites and enterprise platforms.

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