

DETECTION OF MALICIOUS WEBLINKS THROUGH DOMAIN FEATURE EXTRACTION

INTRODUCTION

- Phishing attacks commonly exploit user trust by mimicking legitimate websites using deceptive URLs or weblinks. These weblinks often contain suspicious keywords, recently registered domains, uncommon TLDs, or obfuscated structures designed to bypass traditional security filters.
- This project presents a Chrome browser extension that performs real-time analysis of weblinks to detect phishing attempts. The system extracts structural and contextual features from each URL, such as domain age, special characters, subdomain levels, and lookalike patterns. It classifies each URL as either phishing or legitimate, provides a confidence score, and categorizes it into domains such as financial, e-commerce, or social platforms.
- The tool offers visual warnings, explanations, and historical tracking of phishing detections, enhancing user awareness and enabling a safer browsing experience.

PROBLEM STATEMENT

Despite the prevalence of phishing attacks, current browser defenses are reactive, not proactive — often relying on static blocklists or delayed reputation updates.

Many phishing URLs bypass these defenses by:

- Using newly registered domains with no prior history.
- Obfuscating intent through special characters, excessive subdomains, or IP-based URLs.
- Mimicking trusted services with lookalike patterns (e.g., paypal.com, micr0soft-login.xyz).

Furthermore:

- Most detection systems do not categorize weblinks by domain sector, missing insights into which industries are targeted.
- Real-time alerts, feature-based analysis, and user-side customization are typically absent in available solutions.
- Users lack transparent feedback on why a link is flagged and what makes it risky.

This project addresses these gaps by developing a client-side detection and classification tool that empowers users with actionable insights and timely protection.

LIMITATIONS

1.Blacklist Dependence:

Could only detect previously known phishing URLs; failed against new or evolving attacks.

2. Static Heuristic Rules:

Used fixed rules that lacked adaptability, often resulting in high false positives or negatives.

3. Lack of Real-Time Detection:

Most systems required manual URL input and did not offer real-time browser protection.

4. Limited Dataset Usage:

Many models were trained on small datasets, reducing their effectiveness in real-world scenarios.

SYSTEM ARCHITECTURE

1. User Input Layer (Frontend Interface)

- Component: popup.html, popup.js
- Purpose: Provides an interface for the user to:
 - Input a URL manually or analyze the current browser tab
 - View detection results, settings, and statistics
- UI Tabs:
 - Analyzer Tab: Manual/current URL input
 - Settings Tab: Options like domain age check, TLD alerts, sensitivity
 - Statistics Tab: Shows phishing trends by category/domain
 - History Tab: Lists past detections with time and score

2. Background Logic Layer (Main Engine)

- Component: background.js
- Purpose: Central logic layer that handles:
- Listening to messages from the popup (URL requests)
- Triggering analysis, scoring, classification, and response
- Interfacing with Chrome APIs (tabs, storage, runtime)

3. Feature Extraction Engine

- Component: background.js + utils.js
- Process:
 - Normalize the URL (ensure protocol, extract domain/path)
 - Extract features such as:
 - Domain length, path length, Number of dots, hyphens, digits, equal signs, subdomains, Domain registration age (mocked), Use of IP address or @

4. Scoring and Detection Engine

- Component: background.js
- Apply heuristic-based logic (rule-based model)
- Assign score to each feature (weighted logic)
- Adjust score based on sensitivity level (user-defined)
- Cap score at 0.95, then compare with threshold
- Logic:
 - $\text{score} = \sum(\text{featureWeight} \times \text{multiplier})$
 - $\text{threshold} = 0.3 - ((\text{sensitivityLevel} - 3) \times 0.05)$
 - If $\text{score} > \text{threshold} \rightarrow \text{phishing}$, else legitimate

5. Result Handling and Classification

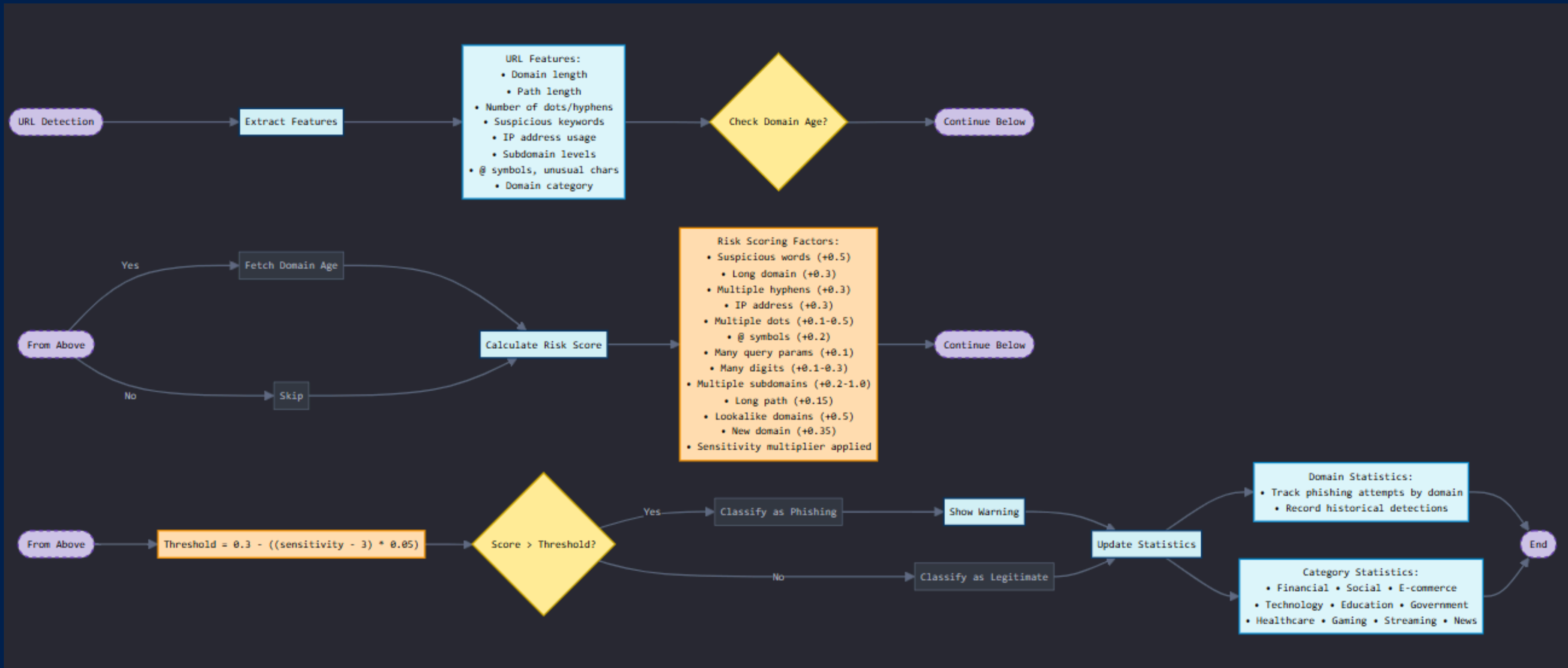
- Component: background.js \rightarrow returns to popup.js
- Result Returned:
 - Final classification: Phishing or Legitimate

- Confidence score
- Risk explanation (why it was flagged)
- Domain category (e.g., finance, social)
- Domain age status
- TLD warning (if present)
- Phishing history for the domain

6. Content Script Action (Page Injection)

- If the analyzed URL is detected as phishing, inject a warning overlay directly into the webpage
- Prevents user interaction unless they choose to proceed

WORKFLOW



PROPOSED SYSTEM

MODULE 1 : PREPROCEESING WITH FEATURE EXTRACTION

Objective: Prepare the input data (URLs) and extract meaningful features for analysis.

Steps Involved:

- Input Handling:
- URLs are fetched and cleaned — removing irrelevant characters or whitespaces.
- Normalization:
- Standardize the format of URLs to avoid inconsistencies (e.g., lowercase conversion, removing http://, etc.).

- Feature Extraction (FE):
- This is the most crucial part. The system analyzes the structure of the URL and extracts multiple features such as:
 - Presence of @ symbol
 - Number of subdomains
 - Number of dots (.)
 - Use of IP address instead of a domain name
 - Presence of suspicious keywords (like login, secure, verify, etc.)
 - Length of the URL
 - Use of HTTPS or not
 - Presence of suspicious characters like -, =, etc.
- Confidence Scoring:
- Based on extracted features, each URL is given a base risk score (initial confidence level). This score becomes the input for the next module.

MODULE 2 : APPLICATION OF ML ALGORITMS

Objective: Analyze the extracted features using machine learning logic to refine the confidence score and detect phishing patterns.

Steps Involved:

- Rule-Based Logic (Mimics ML):
- Even if not a trained ML model, you apply a weighted logic similar to a decision-tree approach:
 - If certain conditions are met (e.g., many dots, presence of suspicious words), the score is incremented.
 - If multiple red flags are detected, the score accumulates accordingly.
 - Mathematical logic like $\text{score} += 0.1 * \min(\text{dots}, 5)$ is used.

- Multipliers:
- Some features (like presence of “@” or IP address) apply multipliers to increase the phishing likelihood score exponentially.
- Thresholding:
- A final threshold (e.g., 0.6 or 60%) is set to distinguish between legitimate and phishing URLs.

MODULE 3 : FINAL URL CLASSIFICATION AND RESULT DISPLAY

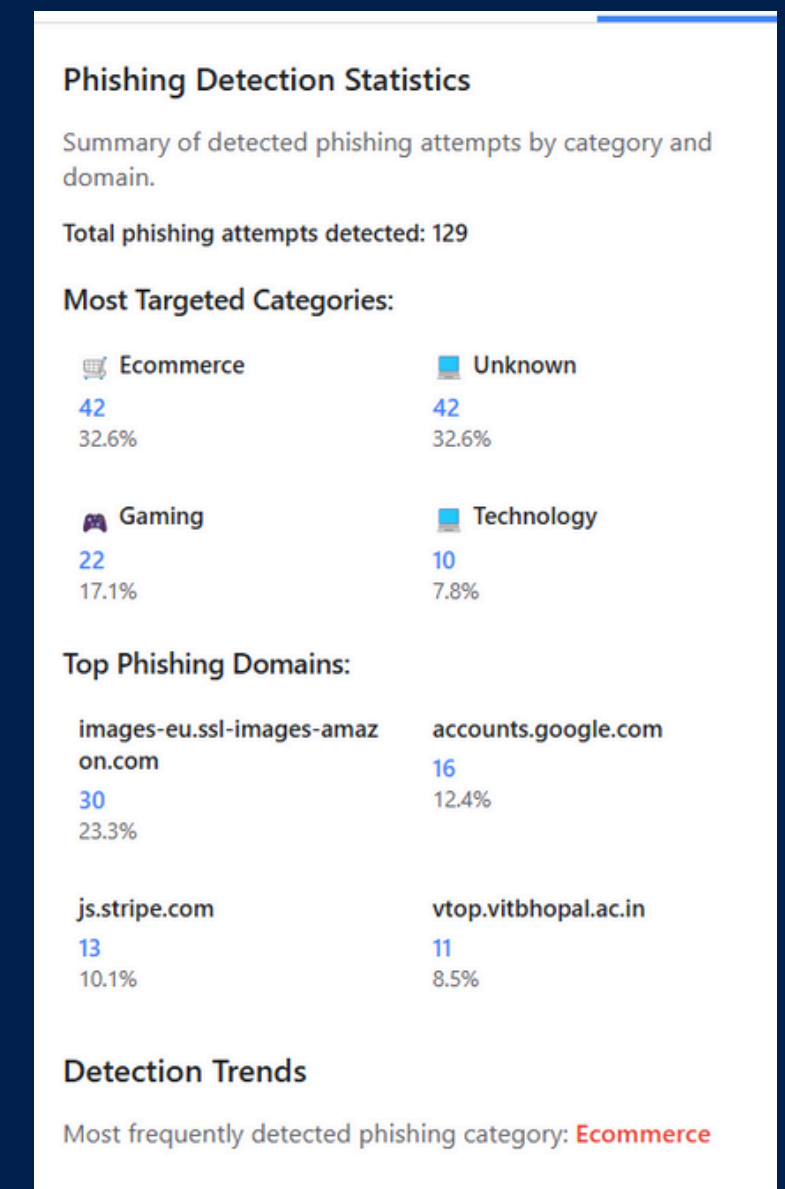
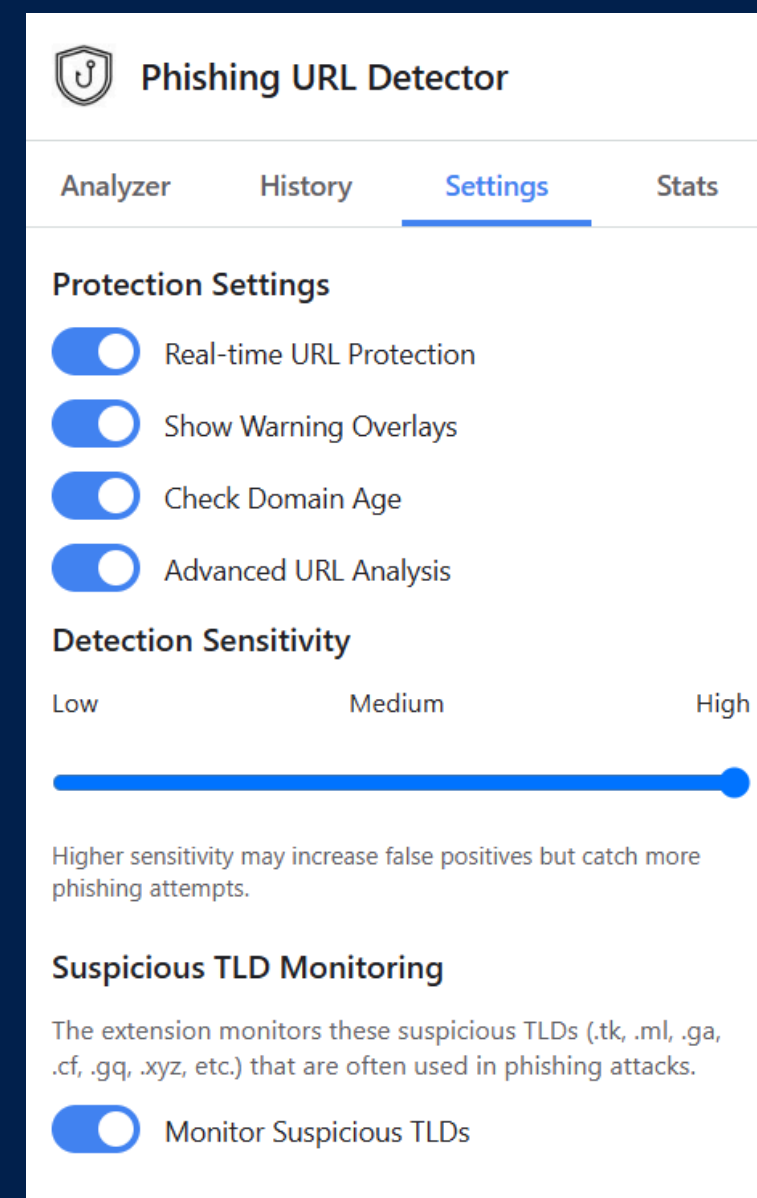
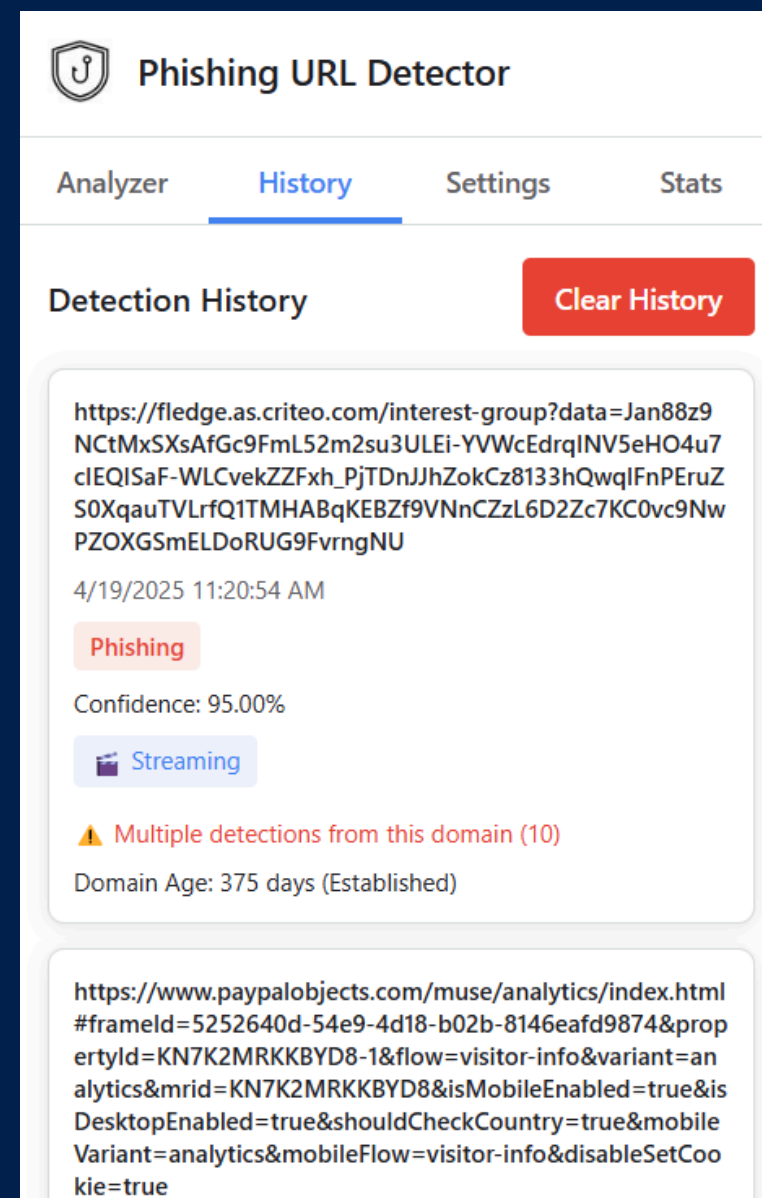
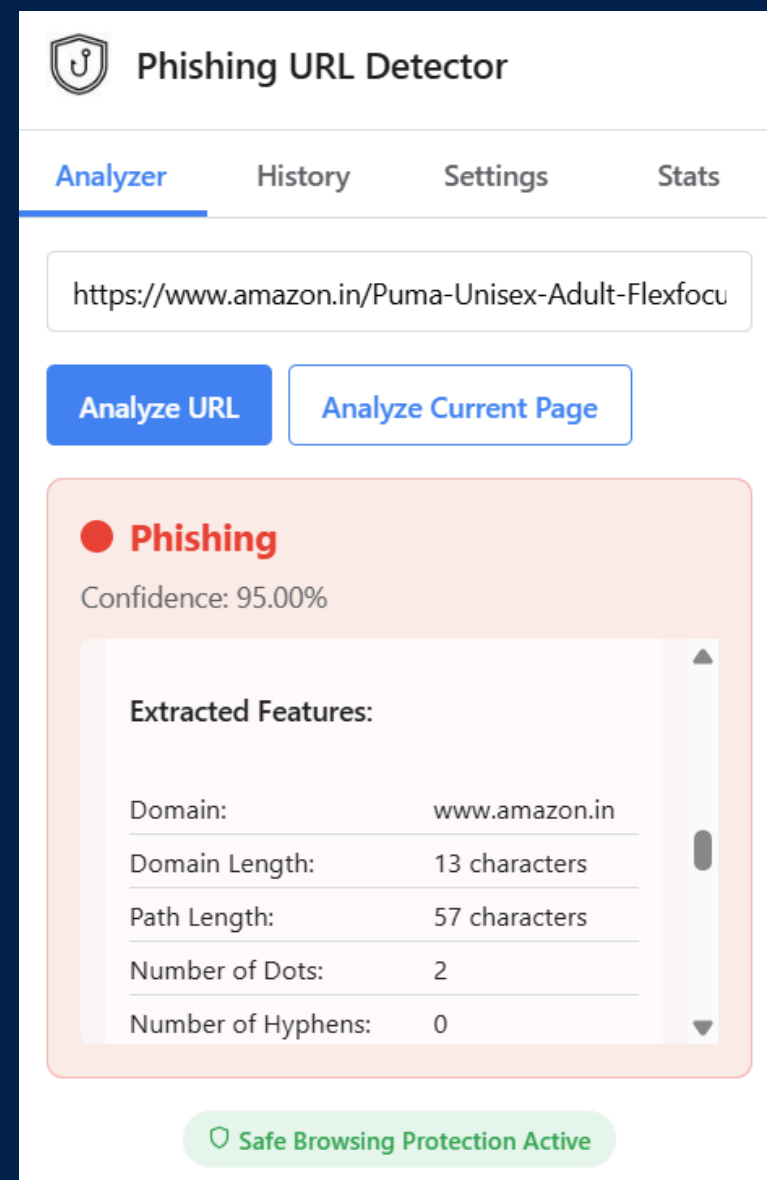
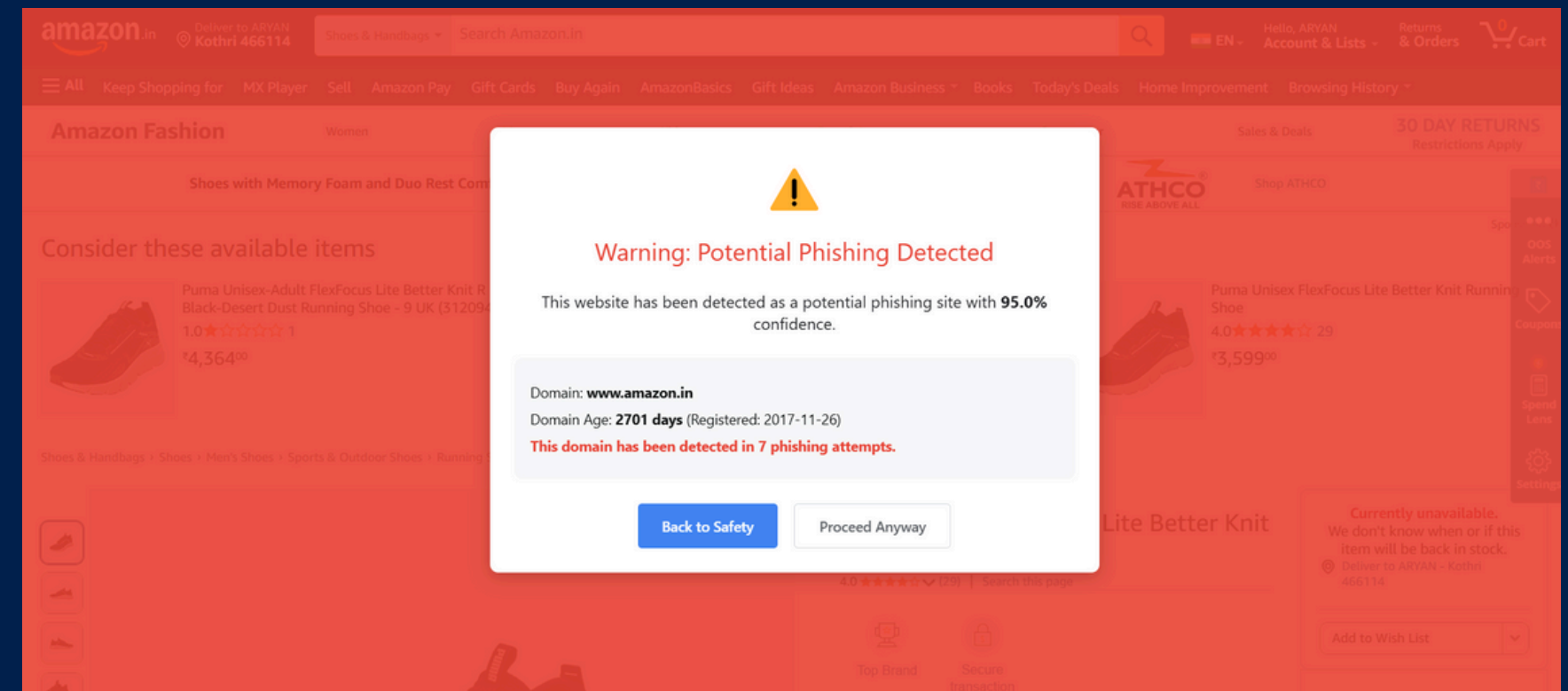
Objective: Use the calculated score to classify the URL and notify the user.

Steps Involved:

- Score Interpretation:
- Based on the total confidence score:
 - Score < 0.4 → Safe
 - Score between 0.4–0.6 → Suspicious
 - Score > 0.6 → Phishing
- Classification Output:

- The result is dynamically shown in the Chrome extension popup using clear labels and colors (e.g., green for safe, red for phishing).
- User Alert:
- Users are alerted about phishing risks and advised to avoid unsafe links.
- Continuous Use:
- Each time a URL is clicked or inspected, the same pipeline is applied.

OUTPUT



REFERENCE

MOHAMMAD, R. M., THABTAH, F., & MCCLUSKEY, L. (2014).
INTELLIGENT RULE-BASED PHISHING WEBSITES CLASSIFICATION.
IET INFORMATION SECURITY, 8(3), 153–160.
DOI: [10.1049/IET-IFS.2013.0202](https://doi.org/10.1049/IET-IFS.2013.0202)

✓ THIS PAPER SUPPORTS THE IDEA OF USING ENGINEERED FEATURES + RULE SCORING FOR PHISHING CLASSIFICATION WITHOUT COMPLEX ML MODELS.

SALVI SIDDHI RAVINDRA, SHAH JUHI SANJAY, SHAIKH NAUSHEENBANU AHMED GULZAR, KHODKE PALLAVI (2021).
PHISHING WEBSITE DETECTION BASED ON URL.
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✓ THIS WORK PRESENTS A SUPERVISED LEARNING MODEL USING URL FEATURES, ALIGNING CLOSELY WITH THE SAME FEATURE LOGIC USED IN OUR BACKEND.

Thank You