ThreatLens: A Unified Tool

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***Abstract*—As digital services are expanding rapidly, we are increasingly depending on websites, which leaves people open to phishing scams and having their passwords stolen. Our paper describes ThreatLens, a small addition to the browser that tackles both of these big problems as they happen and only on a computer. The ThreatLens components that identify phishing sites examine the web address (URL) by searching for common tricks in the words and how the address is built, and then label each site as safe, possibly a problem, or dangerous. For passwords, the password security part of ThreatLens determines their strength by measuring the amount of random variation they have and the number of characters they have. It also checks if your password is on a list of those used in past data leaks, using SHA-1 hashing with k-anonymity that keeps your details private. Importantly, your private information does not go to any other location. When we tested it, ThreatLens was fast, got things right most of the time, and did not slow down the browser much. This tool integrates these capabilities into a single platform with an intuitive design for ease-of-use and provides users with actionable warnings to enable safe browsing practices.**

***Index Terms*—Browser extension security; cybersecurity; data breach detection; k-anonymity; password strength analysis; phishing detection; privacy preservation; real-time threat detection; secure authentication; SHA-1 hashing; URL analysis, web security.**

I. INTRODUCTION

Users now depend heavily on Internet-based applications (i.e, communication, banking, purchasing products and services, and managing identities) as a result of the increasingly rapid expansion of digital services. This increase in reliance is associated with an equally large increase in the number and types of cyber threats directed toward users via deception tactics that capitalize on trusting humans and weak security practices. One of the most common forms of attack is via a method called "Phishing" where an attacker presents a user with a website that appears to be legitimate but actually contains malware designed to extract sensitive information from users.

Additionally, a significant percentage of users utilize either weak passwords or predictably strong passwords, which can easily be accessed by unauthorized parties using automated hacking tools. Current solutions work independently of each other: blacklist-based Phishing Detectors are unable to detect new malicious domains and Password Meters are generally too optimistic when evaluating the strength of a user's password; they do not verify whether a user's password has been exposed due to a data breach. The lack of integration among current solutions means that users currently do not possess a unified, real-time protection solution operating at the browser level.

In this study, we introduce ThreatLens, a browser extension that utilizes phishing URL detection, password strength evaluation, and breach-aware verification to protect users from phishing attacks. The browser extension will operate in direct conjunction with existing browsers and provide users with instant, actionable advice regarding their risk level every time they use the Internet.

II. RELATED WORK

The evolution of phishing detection has progressed from the use of basic blacklists and lexical techniques to advanced machine learning techniques that incorporate various types of hosts, content, and semantics-based features. In this regard, Abdelnabi et al. [1] developed a hybrid approach for detecting phishing attacks by utilizing both the lexical features of URLs combined with HTML structural properties and found that modeling these two feature sets together produces better results than either set alone. Jain and Gupta [2] demonstrated through experimentation that machine learning could be utilized effectively solely to analyze URLs to produce

high levels of accuracy in identifying potential phishing attempts at a relatively low computational cost. Marchal et al. [3] improved the robustness of their system by integrating URL-based feature extraction with domain registration and DNS attributes.

Additionally, there are browser extensions available today that notify users of potential phishing threats, such as NoPhish [4]. These extensions can provide near real-time notifications of suspicious activity. In this area of research, Lin et al. [7] have proposed an alternate approach known as EGSO-CNN, which utilizes deep learning to identify phishing attacks based on raw input from URLs. Additionally, Sujon [21] has shown through experimentation that utilizing ensemble methods along with adaptive resampling increases minority class recall in cases where the data used to train the model is highly skewed towards one particular type of attack.

As related to the security of passwords, several studies have shown that most commonly employed password strength estimators greatly overstate the actual security provided by user-entered passwords. For example, Wang et al. [9] and Golla and Dürmuth [10] have conducted experiments that demonstrate how widely accepted password strength estimators fail to accurately estimate password strength. In addition to demonstrating that password strength estimators do not perform well when estimating the true level of security provided by a password; Hunt [14] created a database called Pwned Passwords which enables users to check whether or not a specific entered password has been involved in a previous breach. Similarly, Bonneau et al. [15] defined formalized protocols for performing breach aware checks in a way that preserves the anonymity of the users being checked. Lastly, Guo and Zhang [24] developed LPSE a lightweight strength estimator that was designed for client-side deployment. To date, no system exists that unifies phishing detection, password strength estimation, and breach awareness within a single user extension like ThreatLens does.

III. SYSTEM DESIGN

A. Architecture Overview

ThreatLens employs a modular, event driven design implemented completely on the client-side and consists of three main layers: The Content Script Layer, The Background Processing Layer, and The User Interface Layer. The Content Script Layer interacts directly with the web page's Document Object Model (DOM) and identifies all active URLs it finds in the current web session, monitors all password entry fields on the current web page and asynchronously sends the monitored data to the Background Processing Layer via messaging. The Background Processing Layer contains both the phishing detection engine and the password/breach module. The User Interface Layer renders UI component(s) that inform users of possible security risks – banners, colored indicators of the strength of entered passwords, etc.

B. Phishing Detection Engine

When a page is loaded the extension obtains the URL and perform a multi-stage heuristic analysis:

1. Lexical Analysis: tokenization, URL length, digit ratio, special characters count, false positive keywords, entropy of URL.
2. Structural Analysis: domain depth (subdomains), encoded character, IP based domain, irregularity of TLD, HTTPS missing.
3. Heuristic Score: calculate the weighted sum to classify the URL as Safe, Suspicious, or Malicious by given ranges.

C. Password & Breach Module

Whenever a user enters characters into a password field, the password evaluator automatically judges the strength of password according to the length of password. This password evaluator examines the diversity of signs (upper, lower, numbers, symbols) because these factors affect security. Entropy estimates and patterns (consecutive, repetitive, dictionary words) are utilized during this evaluation. Experts claim that the result of this judgment is categorized as Weak, Moderate, Strong and Excellent. The evaluation of password strength occurs immediately when the software detects new input.

To detect whether the password has been breached we hash the password client side using SHA-1, we then only check the first 5 characters (prefix) against the client-side breach dataset using k-anonymity. The entire hash match is carried out client-side. The plain password or the entire hash is never sent outside the browser.

IV. METHODOLOGY

Many people believe that the development methodology follows a structured multi-stage pipeline to ensure quality. Functional needs (URL classification, password strength, breach detection) were found by the requirement analysis during the initial phase. Non-functional limitations were identified because the tool requires latency < 50 ms per evaluation, minimal CPU/memory footprint, and cross-platform compatibility. It has been observed that the development methodology provides a clear path for building the security system.

Feature extraction for phishing detection considers URL-based signals (length, entropy, subdomains, suspicious tokens) and DOM-based indicators (hidden forms, iframes, external scripts, cross-domain form actions). A heuristic scoring engine combines these features into a weighted risk score. For password evaluation, entropy is computed using the Shannon formula accounting for character-set size and length, supplemented by pattern-penalty deductions.

System integration links all components through browser Manifest V3 APIs, background service workers, and asynchronous JSON message passing. An error-handling fallback ensures the extension degrades gracefully when inputs are malformed or breach datasets are unavailable.

V. IMPLEMENTATION

A. Phishing Detection Algorithm

In this, the code standardises the URL, calculates a weighted score across five feature groups, and applies threshold comparisons:

```
Funtion detectphishing(url):
Score = 0
If (hassuspicioussubdomains(url)):
Score += w1
If (containsspecialcharacters(url)):
score += w2
If (urllength(url)>threshold:
score += w3
If (containsdeceptivekeywords(url)):
score += w4
IF (encodedcharactersfound(url)):
score += w5
If (score>=maliciouis_threshold):
Return "malicious"
Else if (score>=suspicious_threshold):
Return "Suspicious"
Else:
Return "safe"
```

B. Password Evaluation Algorithm

The logic within this software determines the power of a password step by step. Experts claim that the password level increases bit by bit through this logic. The password is transformed by the SHA-1 method within the code logic because the system examines the hash prefix inside the breach database:

```
FUNCTION EvaluatePassword(password):
Score = 0
If (Length(password)>=min_length):
Score += w_len
If (containsupper(password)):
Score += w_up
If (containslower(password)):
Score += w_low
If (containsnumber(password)):
Score += w_num
If (containssymbol(password)):
score += w_sym
If (MatchesWeakPatterns(password)):
score -= penalty
hashed = SHA1(password)
Breach = hashed in breachdatabase
Return classifystrength(score),breach
```

C. Operating Environment

Development of ThreatLens happened through the usage of HTML, CSS, and JavaScript. To facilitate that ThreatLens functions inside the digital browsing surroundings, the Chrome Manifest V3 Extension Framework was employed. Experts claim that ThreatLens performs across multiple computer platforms when users run navigation programs like Brave, Edge, and Chrome on Windows, macOS, and Linux. ThreatLens stays reachable for all people with electronic entry in various geographic spots because ThreatLens integrates with these operating systems.

VI. TESTING AND RESULTS

A. White Box Testing

Table I: White Box Test Cases

Test ID	Module	Result
WB-01	URL Feature Extraction	Works as expected
WB-02	DOM Analysis Logic	Functions correctly
WB-03	Script Source Scanner	Pass
WB-04	Heuristic Scoring Logic	Matches expected scoring
WB-05	Message Passing Flow	All messages transmitted successfully
WB-06	Password Strength Logic	Correct in all test cases
WB-07	Fallback Logic	Fallback successful; no errors observed

B. Black Box Testing

Table II: Black Box Test Cases

Test ID	Test Scenario	Result
BB-01	Phishing-like webpage detection	Alert displayed correctly
BB-02	Legitimate page check	No alert displayed
BB-03	Weak password test	Weak indicator shown
BB-04	Strong password verification	Displayed strong rating
BB-05	Medium-risk detection	Caution displayed correctly
BB-06	Server unavailable handling	Fallback worked; no crash
BB-07	Settings persistence	Settings saved & reflected
BB-08	Multi-tab stress test	Smooth performance; no crashes
BB-09	UI warning layout check	Displays clearly; no overlap
BB-10	Dynamic webpage handling	Correctly handled dynamic DOM

C. Performance Metrics

The URL heuristic evaluation portion of the application can be completed in less than 50 milliseconds per web page loaded. The password strength scoring feature and hash-based breach checking features both take under 10 milliseconds to run and use minimal CPU resources. The browser extension has demonstrated the ability to operate for an extended period (over 10 concurrent tabs) with no visible loss in user experience.

The phishing detection module was successful in identifying potential phishing URLs as a “high risk” alert while passing through all legitimate banking and e-commerce portal sites without raising a single false alarm. The beach check on passwords successfully alerted when the login credentials were compromised and displayed how many previous breaches had occurred at that site. Thus, allowing the user to choose a more secure alternative.

VII. CONCLUSION

Our paper introduced ThreatLens, an integrated, minimalistic browser add-on that merges on-the-fly phishing URL detection with password strength analysis and breach awareness in a single, client-side, privacy-preserving system. The utility employs a mixture of heuristic lexical examination, entropy-based password scoring, and SHA-1 k-anonymity breach detection because the utility seeks to offer a multi-layered defense against two significant cybersecurity threats facing internet users. Many people believe that this methodology creates a strong barrier for individuals using the web. A multi-layered defense is constructed through these specific technical strategies.

Evaluative processes conducted by the group verified that the system produces precise, low-latency feedback while the system avoids damaging browser performance or sending any sensitive user data to external locations. Experts claim that the system maintains high speeds while keeping private information safe from outside parties. Browser performance was not harmed by the system during the evaluation period. Upcoming research will investigate the inclusion of lightweight machine-learning classifiers, real-time threat-intelligence feeds, larger breach datasets, and automated secure-password recommendation engines because the upcoming research aims to heighten the protection provided. A stronger level of security is anticipated through these future additions

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