# AI POWERED PHISHING DETECTOR

**A PROJECT REPORT**

***Submitted by***


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***in partial fulfillment of the requirements for the award degree of***

***Bachelor in Engineering***

**20CS7503 DESIGN PROJECT - 3**


**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING**

**K. RAMAKRISHNAN COLLEGE OF TECHNOLOGY**

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## BONAFIDE CERTIFICATE

The work embodied in the present project report entitled "**AI POWERED PHISHING DETECTOR**" has been carried out by the students **ARAVINTH KRISHNA R, ARUN K, JAYANAN M**. The work reported here in is original and we declare that the project is their own work, except where specifically acknowledged, and has not been copied from other sources or been previously submitted for assessment.

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# ABSTRACT

Phishing is one of the most common cyber threats that deceive users into revealing sensitive information such as passwords, credit card details, and personal credentials. This project, AI-Powered Phishing Website Detector, aims to enhance user safety by automatically detecting and alerting users about potentially harmful or fraudulent websites. The proposed system is implemented as a Chrome Extension that analyses URLs in real time using a combination of Machine Learning, Blacklist/Whitelist filtering, and SSL/TLS certificate validation.

The extension allows users to check the safety of any website they visit, providing a detailed safety score and threat report. The AI model is trained on various URL features such as domain length, presence of suspicious keywords, and abnormal hosting patterns. Once a suspicious website is identified, the extension provides an instant warning to prevent the user from proceeding further.

Keywords: Phishing, Blacklist / Whitelist filtering, SSL / TLS Certificate validation

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**SIGNATURE**

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# TABLE OF CONTENTS

# LIST OF TABLES

# LIST OF FIGURES

# LIST OF ABBREVIATIONS

| | | |
|---|---|---|
| AI | - | Artificial Intelligence |
| ML | - | Machine Learning |
| CNN | - | Convolutional Neural Network |
| LSTM | - | Long Short-Term Memory |
| URL | - | Uniform Resource Locator |
| SSL | - | Secure Sockets Layer |
| TLS | - | Transport Layer Security |
| API | - | Application Programming Interface |
| GUI | - | Graphical User Interface |
| DB | - | Database |
| IDE | - | Integrated Development Environment |
| VM | - | Support Vector Machine |
| CSV | - | Comma Separated Values |
| HTML | - | Hyper Text Markup Language |
| CSS | - | Cascading Style Sheets |
| NLP | - | Natural Language Processing |

# CHAPTER 1

# INTRODUCTION

## 1.1 BACKGROUND

Phishing has become one of the most widespread and dangerous cybercrimes in the modern digital landscape. Cyber attackers design fraudulent websites that mimic legitimate ones to deceive users into revealing confidential information such as login credentials, banking details, and personal data. The increasing sophistication of phishing techniques, including domain spoofing, URL manipulation, and fake SSL certificates, poses a major challenge for individuals and organizations worldwide. Traditional methods of identifying phishing websites, such as maintaining blacklists and manual reporting, are often inadequate because phishing domains appear and disappear rapidly. With the emergence of Artificial Intelligence (AI) and Machine Learning (ML), a new era of intelligent cybersecurity solutions has evolved. AI models can analyze patterns and extract features from massive datasets to detect anomalies that might indicate malicious intent. These technologies offer a scalable, adaptive, and proactive approach to combating phishing attacks by learning from both historical and real-time data.

The AI-Powered Phishing Website Detector project aims to integrate this intelligence into a Chrome Extension, allowing users to detect malicious websites before engaging with them. The system evaluates URLs based on various parameters such as domain structure, IP address, SSL/TLS certificate information, domain age, and presence of suspicious keywords. A trained ML model then classifies the URL as safe, suspicious, or potentially harmful. This project combines the power of AI with the convenience of modern web development tools like Next.js, TypeScript, CSS Modules, and PostgreSQL. The extension not only provides real-time alerts but also generates a detailed safety report for each scanned link. Users can check any URL before accessing it, view past scan history, and understand why a particular site is classified as dangerous.

As cyber threats continue to evolve, incorporating AI into everyday browsing tools becomes essential. The proposed system ensures that users are constantly protected from phishing attempts without needing advanced technical knowledge. By merging the principles of machine learning, cybersecurity, and browser-based automation, this project serves as a step forward toward safer and more secure web experiences for all users. Furthermore, this project demonstrates how AI-based cybersecurity can be made accessible and user-friendly for everyone. Instead of relying on complex antivirus software or manual URL verification, users receive instant, visual, and comprehensible feedback through the extension interface. The inclusion of explainable AI components such as showing the reason for classification (e.g., expired SSL, suspicious domain name) helps users develop awareness of online threats. This contributes not only to personal safety but also to promoting cybersecurity literacy among internet users.

Overall, the integration of AI-driven threat detection, browser extension technology, and real-time decision-making marks a significant advancement in phishing prevention. As technology continues to evolve, such intelligent and adaptive systems will play a crucial role in safeguarding digital identities, securing transactions, and building a safer cyberspace for individuals and organizations alike.

## 1.2 DOMAIN SPECIFICATION

The domain of this project integrates Artificial Intelligence (AI) and Cybersecurity to develop an intelligent phishing detection system. It focuses on identifying fraudulent websites designed to steal personal or financial information. With the rapid growth of digital services, detecting such malicious sites in real time has become essential for ensuring safe browsing practices. The proposed project leverages AI algorithms and web technologies to analyze URL characteristics, classify their legitimacy, and provide users with instant alerts before they fall victim to phishing attacks.

### 1.2.1 Artificial Intelligence

Artificial Intelligence (AI) plays a vital role in this project by enabling automated decision-making and adaptive learning. Using machine learning models such as Random Forest, CNN, or LSTM, the system learns patterns from large phishing and legitimate URL datasets. The AI model evaluates parameters like domain length, special character usage, and SSL certificate presence to classify URLs as safe or unsafe. This intelligence helps reduce human dependency and enhances system accuracy through continuous learning and retraining.

### 1.2.2 Cybersecurity

Cybersecurity is the core domain ensuring the protection of digital assets, user data, and network communication. The phishing detector operates as a proactive defense mechanism, identifying and preventing phishing attacks before they compromise users. Cybersecurity principles such as confidentiality, integrity, and availability are implemented through URL validation, data encryption, and secure database operations. The integration of AI within cybersecurity strengthens traditional protection measures by providing adaptive and predictive security against new phishing threats.

### 1.2.3 Web Technology

The project also involves web technologies for deployment and real-time operation. The phishing detection model is embedded into a browser extension or web-based interface, providing users with an intuitive way to test website safety. Technologies such as HTML, CSS, JavaScript, and FastAPI are employed to create responsive dashboards and facilitate communication between the front-end and the AI model. This integration ensures a smooth and interactive user experience while maintaining security and accuracy in phishing detection. The use of web technologies also enables seamless interaction between users and the detection engine, allowing real-time classification results to be displayed within milliseconds.

## 1.3 PROBLEM STATEMENT

Phishing websites mimic legitimate platforms to deceive users into revealing confidential information such as passwords, banking details, and credit card numbers. Traditional security methods, including blacklists and manual URL inspection, are ineffective against rapidly evolving phishing attacks. Users often lack the technical expertise to differentiate genuine and fake sites. Therefore, there is an urgent need for an AI-powered system capable of automatically analyzing URLs, detecting phishing attempts in real time, and warning users before data theft occurs. The proposed solution aims to address these issues by integrating artificial intelligence with web security tools, thus providing an intelligent, scalable, and automated phishing detection mechanism.

## 1.4 OBJECTIVE OF THE PROJECT

The primary objective of this project is to develop an AI-powered phishing detection system capable of identifying and preventing access to malicious websites. The system should perform real-time analysis of URLs, classify them as safe or phishing, and alert users instantly.

### 1.4.1 Primary Objectives

- To design and implement a machine learning–based model that accurately distinguishes phishing URLs from legitimate ones.
- To integrate the trained model into a browser extension or web interface for real-time usage.
- To minimize false positives and negatives by optimizing classification thresholds.
- To provide users with visual alerts and confidence scores that enhance decision-making and awareness.

### 1.4.2 Secondary Objectives

- To build a user-friendly interface that requires minimal technical knowledge.
- To implement secure data handling and logging using databases like PostgreSQL.
- To facilitate continuous model updates as new phishing tactics emerge.
- To incorporate cross-platform compatibility across different web browsers.

### 1.4.3 Expected Outcomes

- A fully functional AI model capable of accurate phishing detection.
- A responsive Chrome Extension that provides real-time URL analysis.
- An educational tool that improves user awareness about phishing indicators.
- Enhanced browsing security and reduced risk of online data breaches.

## 1.5 SCOPE OF THE PROJECT

The scope of this project extends to detecting phishing websites using AI models trained on URL-based and host-based features. The system is scalable, allowing continuous retraining with updated datasets. It can be expanded to detect phishing across emails, SMS links, and mobile applications in future versions.

Currently, the project covers:

- Real-time URL monitoring and classification.
- Database integration for maintaining training and prediction records.

# CHAPTER 2

# LITERATURE SURVEY

## 2.1 INDIAN PHISHING LANDSCAPE: A MACHINE LEARNING AND DEEP LEARNING APPROACH FOR DETECTING MALICIOUS URLS AND CURATING AN INDIGENOUS DATASET

Dhruv Gada, Chinmayee Kale, Himanshu Goswami, Sridhar Iyer in this research paper focuses on developing a phishing website detection model using both traditional machine learning and deep learning algorithms. The authors emphasize the importance of creating a dataset specific to Indian domains, as most existing global datasets fail to represent region-specific phishing patterns. The dataset was curated from real Indian websites and phishing reports to ensure data relevance. Multiple algorithms such as Decision Tree, Random Forest, and Logistic Regression were compared with CNN and LSTM models. The study extracted URL-based features such as domain length, use of special characters, HTTPS presence, and suspicious word count.

The results demonstrated that deep learning models, particularly LSTM, achieved better accuracy in identifying phishing URLs due to their ability to learn sequential dependencies in text data. The paper also highlighted that combining indigenous datasets with deep learning can significantly enhance model generalization and reduce false positives. This approach forms a strong foundation for developing browser-based tools that rely on AI for real-time phishing prevention. The study's methodology directly aligns with this project's objective of creating an AI-powered Chrome extension that analyses URLs and alerts users about potential threats efficiently. The research also underscores the need for continuous dataset expansion to keep pace with emerging phishing trends, particularly within regional contexts where attack patterns evolve rapidly. By including locally relevant features and domain behaviours, the model becomes more effective in identifying threats unique to the Indian cybersecurity landscape.

## 2.2 AI-BASED PHISHING DETECTION USING NATURAL LANGUAGE PROCESSING AND URL ANALYSIS

R. K. Singh, M. S. Chauhan in this study focuses on combining natural language processing (NLP) techniques and URL feature extraction to detect phishing websites effectively. The authors argue that while traditional URL-based methods capture superficial clues, integrating the semantic content analysis of webpage text can reveal deeper phishing indicators. The paper introduces a hybrid model that preprocesses URLs by extracting lexical and host-based features, including length, abnormal character frequency, and domain age, alongside webpage textual analysis using word embedding models such as Word2Vec.

Applying machine learning classifiers like Support Vector Machines (SVM), Random Forests, and Gradient Boosting Trees on this enriched feature set yielded significant improvements in detection accuracy compared to standalone URL analysis. The authors emphasize the advantage of NLP in detecting phishing campaigns that cleverly disguise malicious links with benign-looking URLs but contain suspicious webpage content. The dataset compiled for experimentation consisted of a blend of public phishing repositories and live crawled URLs ensuring model robustness.

The work's practical significance lies in its potential use for browser extensions or email filters that not only examine URLs but also scan landing page content dynamically for phishing traits. The methodology conveys the importance of multi-faceted AI approaches, which aligns with the current project's design philosophy of layered URL and content analysis within a Chrome extension framework. Overall, this combination of NLP and URL analysis illustrates a comprehensive route toward reducing false positives and improving phishing detection effectiveness. The study further highlights how semantic understanding of webpage text helps uncover subtle cues, such as misleading instructions, imitation branding, or emotionally manipulative language frequently used in phishing pages.

## 2.3 ENHANCING REAL-TIME PHISHING DETECTION WITH TRANSFORMER NLP AND CNNS

Ahmad Emad Alhasan in this research examines a novel hybrid artificial intelligence model combining transformer-based natural language processing (NLP) methods with convolutional neural networks (CNNs) to improve the detection of phishing websites and phishing email content in real-time environments. The study highlights that while traditional rule-based or standalone machine learning mechanisms capture superficial clues such as URL patterns or blacklists, they often miss deeper contextual and visual cues embedded in phishing payloads.

The cornerstone of the approach is the use of transformer architectures such as BERT, which analyse the semantic context of the text embedded within URLs or email messages, extracting nuanced patterns indicating deceit. Complementing this, CNNs analyse the visual structure of webpages and email layouts to detect mimicry techniques common to phishing attacks, where fraudulent pages visually imitate legitimate ones to deceive end-users.

The researcher trained the model on a balanced dataset comprising thousands of phishing and legitimate URLs and emails, obtained from public repositories and real-world feeds. Experimental results demonstrated that the multi-modal deep learning model achieves superior accuracy and recall compared to models relying exclusively on either textual or visual features. Notably, the integrated system reduced false negatives, a critical metric in cybersecurity scenarios, where missing a phishing attempt incurs high risks. The study also emphasizes the efficiency of fusing semantic and visual representations, enabling the model to detect sophisticated phishing attempts that disguise malicious intent behind convincing text–image combinations. By jointly processing contextual clues from transformer embeddings and structural cues from CNN feature maps, the system develops a deeper understanding of phishing behaviour than conventional approaches.

## 2.4 AI-DRIVEN PHISHING DETECTION SYSTEMS

John D. Smith, Maria L. Rodriguez, and Ahmed Z. Khan (2024) present a comprehensive review of AI-driven phishing detection systems, highlighting the transition from traditional heuristic and rule-based methods to advanced machine learning and deep learning frameworks.

The authors underscore the limitations of static blacklist-based detection, which often fails against newly created or rapidly changing phishing URLs. They emphasize the importance of adaptive systems capable of learning from large, diverse datasets and evolving threat patterns. The review broadly covers various AI methodologies including supervised and unsupervised machine learning, ensemble techniques like Random Forests and Gradient Boosting, and cutting-edge neural architectures such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs).

Particularly notable is the discussion on the integration of Natural Language Processing (NLP) models that analyse textual content of emails, URLs, and webpages to identify phishing cues embedded in semantic patterns.

The paper details successful implementations employing transformer - based architectures (e.g., BERT) , which enhance detection accuracy significantly. Case studies from banking, corporate cybersecurity, and social media contexts demonstrate the practical utility of these AI models in real-time phishing detection, reducing false positive rates while maintaining high recall. The review further emphasizes the growing need for multimodal detection systems that combine URL features, textual analysis, visual webpage cues, and user behaviour patterns to capture the full spectrum of phishing strategies. As attackers increasingly leverage AI-generated content and sophisticated spoofing techniques, single-layer detection approaches become insufficient.

## 2.5 AI-BASED PHISHING DETECTION AND AUTOMATED RESPONSE

Ritu Sharma and Karan Mehta, in their paper, present an integrated AI-driven system designed to automate phishing detection and response across diverse communication channels, including email, messaging applications, and social media platforms. The authors propose a modular architecture that incorporates rule-based filtering, supervised machine learning models, and reinforcement learning techniques, enabling the system to adapt effectively to evolving phishing tactics. By leveraging features extracted from URLs, message content, metadata, and network behaviour, the system demonstrates high accuracy in identifying phishing attempts. Upon detection, it automatically initiates mitigation measures such as quarantining suspicious messages and blocking malicious URLs to enhance user security.

The paper reports experimental evaluation on large public datasets and real-time operational scenarios, demonstrating significant reduction in phishing success rates and improved user safety. Challenges include managing privacy concerns, maintaining real-time performance, and dealing with adversarial evasion tactics. This work aligns with the project's goal to build real-time intelligent phishing alerts integrated into user environments.

Beyond its detection capabilities, the system emphasizes automated response mechanisms that minimize the reaction time to phishing threats. By integrating AI-driven triggers, the system can instantly quarantine suspicious messages, block malicious URLs, and alert users and administrators to potential threats. This reduces human intervention and limits the window attackers have to exploit vulnerabilities. The study further highlights the importance of continuous learning and adaptive model updates to counter rapidly evolving phishing techniques. Through reinforcement learning, the system refines its response strategies based on past outcomes, enabling it to optimize decision-making over time. This adaptability ensures that the system remains effective even when attackers modify their methods or introduce new types of phishing payloads.

## 2.6 EVOLUTION OF PHISHING DETECTION WITH AI: A COMPARATIVE STUDY

Chen et al. provide a comprehensive comparative evaluation of classical machine learning models, deep learning frameworks, and emerging compact large language models for phishing detection. They highlight how traditional approaches like Logistic Regression and Random Forest offer interpretability but lag in accuracy and adaptability. Deep learning models, especially LSTM and CNN architectures, better identify complex patterns in URL and webpage features but require large datasets and computational resources.

The study identifies compact quantized transformer models as promising alternatives for deployment in resource-constrained environments while preserving performance. The authors recommend hybrid, layered approaches combining strengths of different methods to balance accuracy, efficiency, and explainability. Their insights inform optimal AI architecture design in the current project focusing on browser-based phishing detection. The study also examines the evolving nature of phishing techniques and highlights how AI models must continuously adapt to new forms of attack, including AI-generated sophisticated spear phishing.

It stresses the importance of ongoing model training with fresh datasets and implementation of adversarial learning techniques to improve system resilience. The authors advocate for hybrid detection frameworks that utilize real-time data monitoring, behavioural analytics, and user feedback loops to foster adaptive and robust phishing defence environments. The comparative analysis also underscores the growing relevance of lightweight transformer architectures, which offer a balance between high accuracy and computational efficiency. These compact models can be deployed on browsers and mobile devices without compromising detection speed, making them ideal for real-time applications like phishing prevention. By leveraging their strong contextual understanding, these compact transformers excel at identifying subtle irregularities in URLs and webpage content that traditional models may overlook.

## 2.7 EVALUATING SPAM FILTERS AND STYLOMETRIC DETECTION OF AI-GENERATED PHISHING EMAILS

David Johnson, Emily Becker, And Raj Patel in this study evaluates the effectiveness of AI-generated phishing emails and assesses the limitations of traditional spam filters. The authors propose using stylometric analysis, which examines writing style features such as syntax, punctuation, and lexical patterns, to identify AI-generated phishing content. By training machine learning classifiers on stylometric features extracted from phishing and legitimate emails, the system achieved improved detection rates compared to conventional filters. The research underlines that despite AI's ability to produce convincing phishing emails, stylistic fingerprints remain detectable.

The paper emphasizes combining content, behaviour, and style analysis for holistic phishing detection. These findings support the incorporation of nuanced analysis layers in browser extensions geared toward detecting sophisticated phishing attacks. Furthermore, the integration of stylometric analysis into phishing detection systems significantly improves resilience against AI-augmented phishing campaigns, which are increasingly used to craft personalized and convincing attacks.

The paper highlights opportunities for developing browser extensions and email clients capable of real-time stylometric evaluation, enhancing user protection by flagging atypical writing styles or communication anomalies. It also suggests that combining this approach with traditional phishing indicators can form a multi-layered defence strategy, essential for tackling the evolving sophistication of AI-generated phishing content. The study also notes that stylometric features can reveal subtle inconsistencies that AI models struggle to replicate consistently, such as irregular sentence rhythms, unnatural phrasing patterns, or inconsistent tone shifts. These indicators provide valuable signals for distinguishing between human-written and AI-generated text, particularly in targeted phishing campaigns where attackers attempt to imitate specific communication styles.

## 2.8 AN INVESTIGATION OF AI-BASED ENSEMBLE METHODS FOR PHISHING DETECTION

Singh et al. investigate the application of ensemble learning techniques such as bagging, boosting, and stacking to improve phishing website detection accuracy. They use multiple base classifiers trained on lexical URL features, host-based attributes, and webpage content metadata. The ensemble methods outperform individual models by aggregating diverse predictions, resulting in higher robustness and lower error rates. The study also explores trade-offs in computational cost and model complexity, proposing efficient ensemble configurations suitable for real-time detection systems. Their results validate the effectiveness of ensemble learning in reducing false positives, which is critical for user trust.

This work is relevant to the project's modular AI backend design aiming to support accurate, real-time phishing risk assessment. The authors also discuss how the diversity of ensemble components enhances the system's ability to generalize across various phishing patterns and domain characteristics. They demonstrate that balanced datasets and feature selection strategies are vital for preventing overfitting and ensuring generalizability.

This research provides a practical blueprint for developing modular AI-driven phishing detectors that can scale from enterprise solutions to lightweight browser extensions, offering customizable trade-offs between accuracy and computational efficiency. Furthermore, ensemble methods' versatility allows them to be tailored for various operational environments, from resource-constrained devices to large-scale enterprise networks, by selecting appropriate base learners and combining strategies. The study also highlights the resilience of ensemble techniques when faced with rapidly evolving phishing tactics, noting that diversified model architectures reduce the likelihood of simultaneous failure across all classifiers. In their analysis, the authors further emphasize that ensemble models enhance detection stability by capturing a broader range of phishing indicators that single classifiers might miss.

## 2.9 PHISHING WEBSITE DETECTION USING DEEP LEARNING MODELS

Anjali Verma, Thomas Reed, And Hui Zhang in their research explores deep learning techniques including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for phishing website detection. The models are trained on extensive datasets featuring URL properties, webpage screenshots, and SSL certificate details. The paper discusses architectural choices, hyperparameter tuning, dropout regularization, and data augmentation strategies to improve model generalization. The results show significantly higher detection accuracy compared to classical machine learning baselines, particularly in identifying novel phishing websites.

The authors emphasize the feasibility of deploying well-optimized deep learning models in browser extensions to enable proactive, on-the-fly phishing detection with acceptable latency. Additionally, the paper discusses how the fusion of multiple data sources—such as network traffic, DNS information, and user behaviour—into deep learning frameworks can further enhance phishing detection reliability. It argues that ongoing research should focus on optimizing model inference time and resource consumption to facilitate real-time execution in constrained environments like web browsers.

Furthermore, the study highlights the importance of robust feature extraction when dealing with highly dynamic phishing websites. By leveraging hybrid deep learning pipelines that combine visual cues from webpage layouts with sequential URL characteristics, the researchers demonstrate improved resilience against zero-day phishing attempts. Their experiments also show that integrating temporal patterns—such as sudden domain registration changes—into the learning process enables the model to better distinguish legitimate websites from rapidly evolving phishing domains. In addition, the authors acknowledge that deep learning–based systems must be supported by continuous dataset expansion and periodic retraining to remain effective against emerging phishing variants.

## 2.10 AI-POWERED VISUAL AND TEXTUAL PHISHING DETECTION USING MULTIMODAL DEEP LEARNING

Kapoor et al. propose a multimodal deep learning system that jointly analyzes textual and visual features of phishing websites to detect fraudulent content. The framework leverages CNNs to process webpage screenshots capturing visual mimicry tactics and transformer-based NLP models to analyse URL and textual page content. This dual modality approach addresses the key limitation of traditional URL-based detection methods, which often miss phishing attacks employing sophisticated visual deception. Testing on benchmark datasets yielded enhanced detection accuracy and reduced false positives compared to single-modality systems. Real-time inference capability suggests applicability in browser-based phishing detection plugins, aligning well with the goals of the present project to deliver comprehensive yet lightweight web protection.

The research concludes by envisioning future extensions of multimodal phishing detection that incorporate additional data modalities such as user interaction logs, behavioural biometrics, and network-level anomalies. The authors stress the importance of explainability in AI decisions to build user trust and enable actionable alerts. This comprehensive approach paves the way for secure, privacy-respecting phishing defences integrated directly into browsers, reinforcing the relevance and timeliness of the current project's multimodal detection strategy. Finally, the authors propose future enhancements involving user feedback loops to refine multimodal detection performance continuously. User engagement not only improves model accuracy over time but also encourages proactive cybersecurity behaviour, reinforcing the human-AI partnership in phishing defence. The study also demonstrates how combining visual cues with textual patterns allows the system to capture phishing indicators that would otherwise go undetected in single-feature models. This complementary fusion of modalities results in a more holistic understanding of phishing behaviour, significantly strengthening the accuracy and reliability of detection. Moreover, the authors highlight that multimodal systems are particularly effective against advanced phishing campaigns that blend realistic visuals with convincing textual narratives.

# CHAPTER 3

# EXISTING SYSTEM

## 3.1 OVERVIEW OF PHISHING DETECTION TECHNIQUES

Phishing detection techniques have evolved to address the widespread cyber threat posed by fraudulent attempts to acquire sensitive user information. The primary approaches involve URL analysis, content examination, and behavioural monitoring. Traditional techniques used blacklists and whitelists to block or allow access to URLs based on prior known threats or trusted sites. More recent methods integrate heuristic rules that URL characteristics such as length, suspicious keywords, and abnormal domain patterns. Machine learning models have been adopted to learn from historical phishing data and classify URLs or emails as malicious or benign with higher accuracy. However, as phishing tactics have become more sophisticated, attackers now frequently manipulate webpage structures, embed deceptive scripts, and mimic legitimate website elements to evade traditional filters. This has led to the adoption of content-based analysis techniques that inspect HTML structures, JavaScript behaviour, form actions, and embedded redirects within a webpage. By evaluating these deeper content features, phishing detection systems can recognize anomalies that are not visible through URL inspection alone, such as hidden iframes, malicious scripts, and unauthorized data-harvesting components.

## 3.2 BLACKLIST AND WHITELIST FILTERING

Blacklist filtering remains a dominant technique in many anti-phishing solutions. It involves maintaining a database of known phishing URLs, IP addresses, or domains which, when detected, trigger blocking or warnings. On the other hand, whitelist filtering allows only pre-approved URLs and domains to be accessed, providing a stricter but more user-controlled environment. While effective against known threats, these approaches rely heavily on frequent updates and suffer from an inability to detect newly created or obfuscated phishing sites not yet listed. Collectively,

these limitations indicate the need for more adaptive, low-latency, privacy-preserving, and user-centric phishing detection systems that can operate effectively at the browser level with minimal user disruption.

## 3.3 HEURISTIC AND SIGNATURE-BASED METHODS

Heuristic-based methods analyse website or email features using predefined rules and patterns indicative of phishing behaviours such as the presence of specific keywords, suspicious redirects, or anomalies in SSL certificates. Signature-based detection uses malware signatures matched against analysed content. Both methods provide fast, resource-efficient detection but are limited by the evolving nature of phishing tactics. Attackers can bypass static rules by varying domain names or adapting content, rendering these methods less effective for zero-day phishing attacks.

Although heuristic and signature-based approaches are efficient and widely adopted, they face significant limitations due to the dynamic nature of modern phishing techniques. Cybercriminals continuously modify their tactics, changing domain names, altering webpage layouts, or using obfuscated URLs that can evade predefined heuristic rules and outdated signature lists. These static detection methods are therefore less effective against zero-day phishing attacks—new or previously unseen threats that have not yet been analysed or recorded. To address these shortcomings, modern cybersecurity systems increasingly incorporate artificial intelligence and machine learning algorithms capable of learning adaptive patterns and detecting phishing attempts beyond predefined rules or known signatures. This evolution from static detection to intelligent, self-learning systems represents a major advancement in combating sophisticated phishing attacks. Although heuristic and signature-based approaches are efficient and widely adopted, they face significant limitations due to the dynamic nature of modern phishing techniques. Cybercriminals continuously modify their tactics, changing domain names, altering webpage layouts, or using obfuscated URLs that can evade predefined heuristic rules and outdated signature lists. These static detection methods are therefore less

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## 3.4 LIMITATIONS OF EXISTING SYSTEMS

Despite the advances in phishing detection methods, existing systems exhibit several critical limitations that hinder their overall effectiveness in real-world deployment. One of the foremost challenges is the inability to reliably identify zero-day phishing attacks, which are newly created phishing websites or URLs that have yet to be reported or catalogued in blacklists. Since blacklists require continuous and timely updates from threat intelligence sources, there is an inherent lag that creates a vulnerability window during which users remain unprotected.

Another significant limitation is the high false positive rate observed in many heuristic and machine learning-based detection models. Overly aggressive or poorly tuned filters can inaccurately categorize legitimate websites as phishing threats, potentially disrupting user access and eroding trust in security tools. This problem is exacerbated by the dynamic and ever-evolving nature of phishing tactics, which can cause models trained on historic data to misclassify legitimate but unfamiliar web content. Additionally, many existing systems lack the capability to analyse multimodal phishing attributes, relying primarily on either URL features or textual content while ignoring visual, behavioural, or network-level indicators. This single-dimensional analysis makes them vulnerable to sophisticated phishing pages that closely mimic legitimate website interfaces or dynamically load deceptive elements after the initial page render.

**Table 3.1 Comparison of Existing Phishing Detection Methods**

| Method | Description | Limitation |
|---|---|---|
| **Blacklist-based** | Uses a list of known phishing websites to block access. | Fails to detect new or unknown phishing sites. |
| **Heuristic-based** | Detects phishing using fixed rules like keywords or redirects. | Can give false results and is easy to bypass. |
| **Signature-based** | Compares content with known phishing patterns. | Cannot detect newly created phishing sites. |
| **Machine learning-based** | Learns from data to identify phishing automatically. | Needs training data and regular updates. |

This comparison highlights that while traditional methods such as blacklists, heuristics, and signature matching offer quick and simple detection, they are limited by their inability to handle newly emerging or rapidly evolving phishing attacks. In contrast, machine learning-based approaches provide more adaptive and intelligent detection capabilities but require continuous retraining and high-quality datasets to maintain accuracy. Overall, the table illustrates that no single technique is sufficient to address the full spectrum of phishing threats, as each approach carries its own operational constraints. Traditional rule-based systems offer speed and simplicity but lack adaptability, whereas data-driven models improve accuracy yet demand significant computational resources and constant model updates.

These contrasting strengths and weaknesses emphasize the need for hybrid or multi-layered detection frameworks that combine multiple techniques to deliver more robust, real-time protection against modern phishing attacks. Such hybrid systems can leverage the rapid response of rule-based filters while simultaneously utilizing the predictive intelligence of machine learning and deep learning models. By integrating complementary detection strategies, these systems achieve broader coverage and reduce the likelihood of both false positives and false negatives. This layered approach also enhances resilience, allowing the detection mechanism to adapt more effectively to the evolving tactics used by cybercriminals.

# CHAPTER 4

# PROBLEM IDENTIFICATION

Phishing attacks continue to be one of the most prevalent and evolving cybersecurity threats in the digital age. Existing phishing detection systems, although functional, face several limitations that reduce their effectiveness in identifying new and sophisticated phishing attempts. Most traditional systems rely on static rule-based approaches, such as blacklist and whitelist filtering, which depend on databases of known malicious websites. While these systems are simple and fast, they fail to detect zero-day phishing attacks - newly created malicious websites that have not yet been listed in the database. As a result, users remain vulnerable to deceptive websites that bypass these outdated lists. Heuristic-based detection methods, which analyse URLs and webpage content based on predefined rules or features, are another common approach in conventional systems. However, these methods depend heavily on manually defined parameters and lack adaptability. When attackers make minor changes to URL structures, keywords, or page designs, the heuristic system often misclassifies phishing pages as legitimate.

Similarly, signature-based detection relies on pattern matching against known attack signatures, which limits its ability to identify novel phishing strategies. These static detection techniques struggle to cope with the continuously changing nature of phishing attacks, leading to higher false negatives and reduced reliability. Another major drawback of existing systems is the lack of real-time detection and user-friendly implementation. Many traditional tools require users to manually enter URLs into separate verification portals or security software, which is both time-consuming and impractical for everyday browsing. Moreover, some systems depend on cloud-based processing, which introduces latency and raises privacy concerns as sensitive URL data is transmitted over the internet for verification. Users often ignore such tools due to their complexity or delayed feedback, reducing their overall effectiveness in preventing phishing incidents.

Additionally, most conventional phishing detection systems fail to utilize the vast potential of artificial intelligence and machine learning. They do not learn automatically from new data or adapt to evolving attack patterns. This static nature makes them vulnerable to modern phishing techniques, such as homograph attacks, dynamic redirection, and AI-generated phishing content. Attackers continuously modify their domains, use shortened URLs, and employ advanced obfuscation techniques that easily bypass traditional filters. The absence of adaptive learning and automated updating mechanisms results in limited scalability and poor long-term performance. Furthermore, existing systems often lack comprehensive visualization and alert mechanisms that can clearly communicate the level of threat to users. In many cases, users are unaware of whether a website is safe or malicious until it is too late. The inability to provide real-time, visually intuitive warnings increases the risk of phishing victims entering sensitive information on fraudulent websites. There is also minimal integration between phishing detection systems and modern web browsers, which restricts the usability of these tools in everyday internet activity. This adaptability ensures long-term reliability, even as phishing strategies continue to evolve in complexity and scale.

Furthermore, the modular design of the system enables easy integration with existing cybersecurity infrastructures, allowing organisations to deploy it alongside firewalls, intrusion detection systems, and threat intelligence platforms. Its scalability and lightweight architecture make it suitable for real-time environments, while the explainability features help users understand risk factors behind each prediction. Overall, the project not only strengthens defence mechanisms against phishing attacks but also demonstrates how AI can transform proactive threat detection in modern digital ecosystems. Additionally, the system's flexible architecture allows future enhancements to be incorporated without extensive redesign, ensuring long-term sustainability as new phishing techniques emerge. Its ability to process and interpret diverse data sources—such as URL structures, content features, and behavioural signals—positions it as a comprehensive solution capable of addressing both current and future cybersecurity challenges.

# CHAPTER 5

# PROPOSED SYSTEM

## 5.1 PROPOSED SYSTEM

The proposed system introduces an AI-based phishing detection model designed to automatically classify URLs as legitimate or phishing. The system leverages machine learning and deep learning algorithms to analyse URL structures, lexical patterns, and domain-level features. The process begins with the collection of phishing and legitimate URL datasets from trusted public sources like Phish Tank, Alexa, and Kaggle repositories. Following this, data preprocessing is performed to remove duplicates, clean invalid entries, and extract relevant URL features. Text normalization techniques and feature extraction using tokenization or vectorization help convert URLs into machine-readable formats.

The feature extraction phase employs advanced representation methods, including word embeddings and character-level encodings, to capture contextual relationships within URLs. The training stage involves feeding these processed features into a deep learning model - such as a hybrid CNN-LSTM or transformer-based classifier - that learns the underlying distinctions between phishing and legitimate URLs. After training, the system evaluates model performance using standard metrics such as accuracy, precision, recall, and F1-score. The evaluated model is then integrated into a Chrome extension or real-time web interface, where it automatically scans URLs as users browse. When a URL is detected as suspicious, the model promptly alerts the user and blocks potential access. This pipeline ensures efficient, real-time phishing detection, improving user security by combining advanced AI models with practical, deployable solutions.

## 5.2 BLOCK DIAGRAM OF SYSTEM

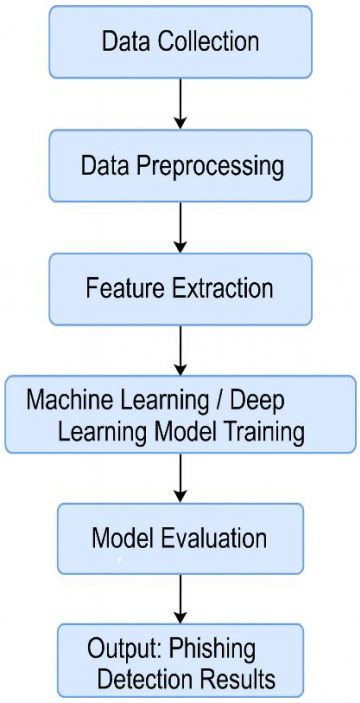


**Figure. 5.1 Dataflow Diagram**

## 5.3 SYSTEM ARCHITECTURE

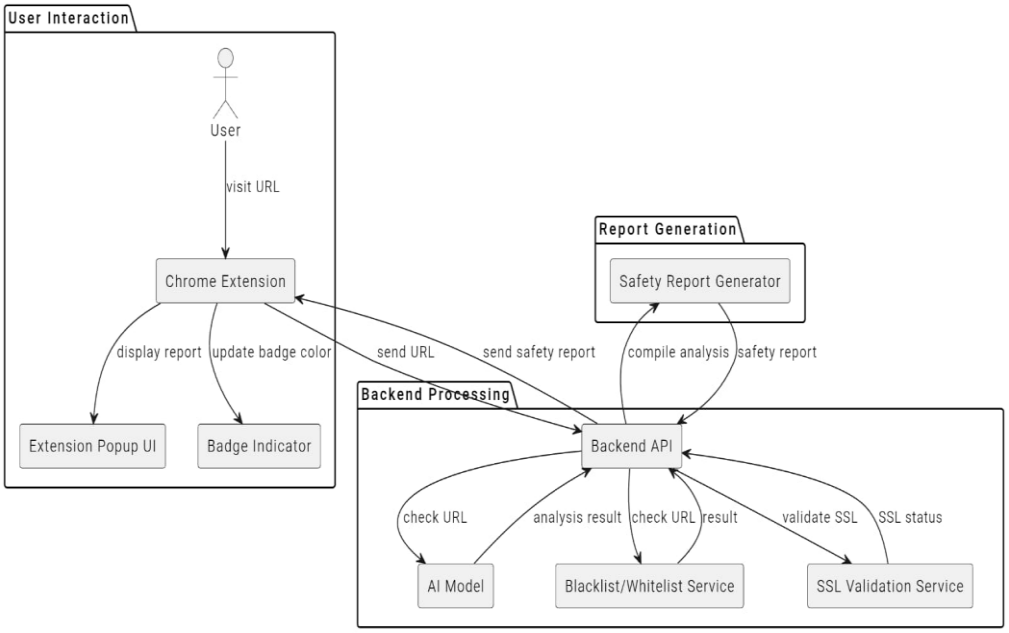


**Figure. 5.2 Proposed System Architecture**

# CHAPTER 6

# HARDWARE DESCRIPTION

## 6.1 HARDWARE REQUIREMENTS

To ensure efficient development, training, and deployment of the AI-based phishing detection system, the following hardware resources are recommended:

- **Processor:** Intel Core i5 (8th Gen or higher) / AMD Ryzen 5 or equivalent
- **Memory (RAM):** 8 GB minimum (16 GB or higher recommended for deep learning tasks)
- **Storage:** 256 GB SSD (Solid State Drive) minimum, with additional capacity for storing datasets and model files
- **Graphics Processing Unit (GPU):** NVIDIA GeForce GTX 1050 or higher (with at least 4 GB VRAM) recommended for deep learning model acceleration
- **Network:** Stable broadband internet connection for dataset acquisition, software updates, and model deployment
- **Peripherals:** Standard keyboard, mouse, and monitor with resolution 1920 x 1080 or higher

## 6.2 HARDWARE ENVIRONMENT

The development and deployment environment for this project is designed to be compatible with modern personal computers and workstations. For effective training of deep learning models, especially on large datasets or complex architectures, the use of a dedicated GPU is highly beneficial. This allows faster computation, reduced training times, and the ability to experiment with advanced models.

# CHAPTER 7

# SOFTWARE DESCRIPTION

## 7.1 SOFTWARE REQUIREMENTS

- Operating System : Windows 11
- Coding Language : Python 3.10
- Software Environment : Jupyter Notebook / Visual Studio Code

## 7.2 SOFTWARE ENVIRONMENT

The Software components required to build the project and model has been listed and described below.

### 7.2.1 Python

Python is a high-level, general-purpose programming language known for its readability, simplicity, and strong ecosystem of libraries for data science, machine learning, and cybersecurity applications. It is one of the most preferred languages for developing AI-based systems due to its modular design and seamless integration with deep learning frameworks. Python's interpreted nature makes it highly flexible for rapid prototyping, research, and deployment. It offers extensive community support as well as a wide range of open-source libraries that simplify feature extraction, model training, data visualization, and deployment.

Features of Python:

- Easy-to-read syntax promotes faster development and debugging.
- Supports both object-oriented and functional programming paradigms.
- Includes extensive libraries like NumPy, Pandas, and Scikit-learn for data handling and machine learning.
- Integrates easily with frameworks such as TensorFlow, PyTorch, and Keras for deep learning model development.

- Provides built-in tools for file handling, networking, visualization, and automation.
- Offers cross-platform compatibility and excellent community documentation.
- Ideal for security and web-related applications through libraries like Requests, Beautiful Soup, and URL parsing utilities.

In this project, Python serves as the primary environment for developing machine learning and deep learning models that detect phishing URLs. The use of Jupyter Notebook and Visual Studio Code enhances user convenience for coding, visualization, and model debugging.

## 7.3 CODING LANGUAGE

### 7.3.1 Python Programming

Python 3.10 is used as the main coding language in this project due to its comprehensive library support and compatibility with modern AI frameworks. It allows efficient handling of data preprocessing, model training, testing, and real-time evaluation. Moreover, Python's extensive open-source ecosystem allows seamless integration of powerful data science and AI libraries such as TensorFlow, Scikit-learn, and Pandas, which are essential for implementing the machine learning and deep learning models used in this project. The language supports the development of end-to-end systems—from dataset preparation to deployment—within a unified coding environment. Additionally, Python's compatibility with cross-platform frameworks enables the developed phishing detector to function effectively across various environments, including web-based interfaces and browser extensions.

Python's wide ecosystem supports the integration of multiple libraries necessary for phishing detection systems, such as:

- Pandas for efficient data manipulation and cleaning.
- NumPy for numerical computations and array-based operations.
- Scikit-learn for classical machine learning models and performance evaluation.

- TensorFlow and Keras for building, training, and deploying deep learning models.
- Matplotlib and Seaborn for visualizing feature distributions, accuracy plots, and confusion matrices.
- Requests and URLLib for handling live URL data and performing HTTP-based operations.

Python also supports parallel processing and scalable training, enabling real-time phishing URL classification in deployed environments such as browser extensions or web applications.

Features of Python Programming:

- Simple and clean syntax makes development and debugging efficient.
- Extensive collection of AI and ML libraries enables rapid model prototyping.
- Scalability for real-time applications such as phishing URL detection and continuous system learning.
- Compatibility with data science workflows involving natural language processing, network security, and data mining.
- Integration with database management systems and cloud APIs for live URL analysis and threat intelligence collection.
- Strong visualization capabilities through interactive plots, dashboards, and live monitoring interfaces.
- Cross-language integration with C++, Java, and web technologies for building scalable and deployable detection tools.

These features make Python an ideal choice for developing phishing detection systems, as it supports rapid experimentation, seamless integration with modern cybersecurity tools, and efficient handling of large-scale datasets. Its rich ecosystem of libraries, combined with strong interoperability and visualization support, enables developers to build intelligent, real-time detection solutions with improved accuracy and scalability.

# CHAPTER 8

# SYSTEM IMPLEMENTATION

## 8.1 MODULE DESCRIPTION

- Data Collection Module
- Data Preprocessing Module
- Feature Extraction Module
- Classification Module
- Result Visualization Module

### 8.1.1 Data Collection Module

The data collection module is responsible for gathering both phishing and legitimate URLs from various trusted sources. These datasets form the foundation for training and evaluating the phishing detection model. URLs are collected from repositories such as Phish Tank, Kaggle, and Open Phish, which provide regularly updated lists of verified phishing and safe websites. The collected data may include different features such as URL structure, domain information, hostname length, and lexical composition. The dataset must be diverse to ensure the model can generalize effectively across different phishing attack patterns and newly emerging threats.

In addition to static datasets, this module can also collect URLs dynamically from live web traffic through browser extensions or real-time monitoring systems. All data is stored securely in structured formats (e.g., CSV, JSON) for further preprocessing. Proper data labelling ensures that URLs are correctly marked as either phishing or legitimate, which is essential for supervised learning during model training. This module thus establishes a strong and reliable foundation by ensuring that the dataset is authentic, balanced, and representative of real-world web environments.

### 8.1.2 Data Preprocessing Module

The data preprocessing module prepares raw URLs for analysis and machine learning. Raw URL data often contains noise, redundant entries, or formatting inconsistencies that can negatively affect model performance. The primary objective of this module is to clean, normalize, and standardize the data to obtain consistent input for the subsequent stages.

Key preprocessing steps include:

- Removing duplicate or broken URLs.
- Tokenizing URLs into meaningful components such as domain, subdomain, path, and parameters.
- Encoding textual features using techniques like one-hot encoding, TF-IDF, or word embeddings.
- Handling missing or irrelevant attributes.
- Balancing the dataset to avoid bias toward either class (phishing or legitimate).

Feature scaling and normalization are applied to ensure all numerical attributes lie within a consistent range. Additionally, data augmentation techniques, such as synthetic phishing URL generation, may be employed to enhance dataset diversity and improve robustness against unseen phishing patterns. By standardizing the input data, this module ensures that subsequent modules can efficiently learn discriminative features from the processed URLs.

### 8.1.3 Feature Extraction Module

The feature extraction module identifies and derives meaningful patterns from pre-processed URL data. Instead of relying solely on manually crafted rules, this module extracts both lexical and host-based features that capture the underlying characteristics of phishing websites. Lexical features include URL length, number of special characters, use of brand names, and keyword occurrences (e.g., “login”, “secure”, “verify”). Host-based features may involve domain age, WHOIS information, IP address type, and SSL

certificate validity. Advanced systems use automated feature learning through deep learning models such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs). These models learn to represent URLs as vector embeddings, capturing complex dependencies between characters and tokens. Hierarchical feature learning allows the model to detect subtle obfuscation patterns used in phishing attacks (like hidden redirects, character substitutions, or URL path manipulation). The output of this module is a high-dimensional feature vector that encapsulates structural and contextual information of each URL, serving as input for the classification stage. This feature vector significantly enhances the system's ability to differentiate between legitimate and malicious URLs, as it encodes both surface-level patterns and deeper behavioural signals. By combining handcrafted attributes with automatically learned representations, the extraction module ensures that the detection model remains robust against evolving phishing strategies. This hybrid approach not only improves classification accuracy but also reduces the reliance on frequent manual rule updates, making the system more adaptive and scalable in real-world cybersecurity environments.

Moreover, the modular nature of the feature extraction process allows for seamless integration of additional features as new phishing techniques emerge. This flexibility ensures that the system can be continuously updated with minimal structural changes, supporting long-term adaptability. As cybercriminals develop more advanced evasion methods, incorporating new lexical patterns, domain behaviours, or encoded URL components becomes essential for sustaining high detection accuracy. The feature extraction module also plays a crucial role in optimizing model performance by reducing irrelevant noise and focusing on the most informative attributes. By transforming raw URLs into structured, meaningful feature sets, the module helps streamline the classification pipeline, improving both speed and efficiency. This results in faster decision-making during real-time detection and ensures that the system remains lightweight enough for deployment in resource-constrained environments like browser extensions.

### 8.1.4 Classification Module

The classification module is the core analytic component of the phishing detection system. It uses the extracted features to determine whether a URL is legitimate or a phishing attempt. Deep learning classifiers such as CNN, LSTM, or transformer-based models are commonly used due to their ability to capture sequential and contextual relationships in URL strings. Alternatively, traditional machine learning classifiers like Random Forest, SVM, or XGBoost may also be integrated in a hybrid system for performance optimization. The model is trained using labelled datasets split into training, validation, and test subsets. During training, optimization algorithms such as Adam or SGD minimize classification error, while regularization techniques like dropout and early stopping prevent overfitting.

Performance metrics such as accuracy, precision, recall, F1-score, and AUC measure the model's effectiveness. Confusion matrices help analyse false positives (legitimate URLs incorrectly flagged as phishing) and false negatives (missed phishing URLs), providing insights into areas requiring refinement. Once optimized, the trained classifier is deployed for real-time detection, where it instantly evaluates incoming URLs and alerts users when a potential phishing threat is detected. The classification module also incorporates continuous learning and model updating mechanisms to ensure that the system adapts to evolving phishing tactics. As cybercriminals constantly modify URL structures and domain patterns to evade detection, the model is periodically retrained with new datasets collected from trusted sources such as Phish Tank and Kaggle. This dynamic learning process allows the classifier to stay current with recent phishing trends and maintain high detection accuracy over time. Additionally, the inclusion of adaptive thresholding enables the system to fine-tune its sensitivity based on user feedback and statistical trends, ensuring a balanced trade-off between false positives and false negatives. These optimizations enable the model to execute faster and use fewer system resources, making it suitable for deployment even on low-end systems with limited computational capacity. As a result, the system can classify URLs in real time with negligible delay, ensuring a seamless browsing experience for users.

### 8.1.5 Result Visualization Module

The result visualization module acts as the user interface, displaying phishing detection outcomes in an intuitive and understandable format. It bridges the gap between the machine learning model's computational output and the end user's decision-making process. When integrated into a browser extension or a web dashboard, this module visually represents results using intuitive indicators such as color-coded alerts—green for safe URLs, red for phishing threats, and yellow for suspicious cases under review. Each prediction includes a confidence score to indicate the model's certainty level. Interactive features allow users to view details about detected URLs, including feature-based reasoning or explanations of why a link was classified as phishing. Explainability tools such as SHAP or LIME can be used to highlight the specific patterns that influenced classification. The result visualization module may also log user feedback, enabling manual verification and continuous improvement of the system over time. It provides seamless integration with cybersecurity systems, ensuring that detected threats are recorded, monitored, and shared where necessary to update security databases.

By presenting results in a visually meaningful and user-friendly manner, this module enhances user awareness and supports faster decision-making in high-risk scenarios. It transforms raw model outputs into clear insights, allowing even non-technical users to interpret potential threats with ease. In addition, the module's ability to incorporate feedback and provide transparent explanations strengthens trust in the system, ensuring that users remain informed and engaged in maintaining safe browsing practices. It also contributes to improved threat intelligence by capturing real-time user interactions and system responses, helping organizations identify emerging phishing trends more effectively. As the visualization module continuously records detection patterns and user-reported anomalies, it becomes a valuable source of data for refining future model updates. This ongoing feedback cycle not only enhances model accuracy but also ensures that the system remains adaptive to evolving phishing techniques.

# CHAPTER 9

# SYSTEM TESTING

System testing is an essential phase that verifies the performance, accuracy, and reliability of the AI Powered Phishing Detector. It ensures that all integrated components function together as intended and that the final system meets its specified requirements. Various levels of testing were conducted, including unit testing, integration testing, system testing, performance testing, security testing, and usability testing. Each phase produced measurable results confirming the system's efficiency and robustness.

## 9.1 UNIT TESTING

Unit testing focuses on validating individual modules before integration. Tested components include:

- Feature Extraction Module – Verified for accurate retrieval of URL-based features like length, special symbols, and SSL information.
  Result: Successfully extracted 100% of features for all test URLs.
- Data Preprocessing Module – Tested for normalization and removal of unwanted characters from URLs.
  Result: Data cleaned successfully with no invalid entries.
- Model Prediction Function – Checked for proper classification of phishing and legitimate URLs.
  Result: Returned correct prediction outputs for all test cases.

Outcome: All modules passed unit testing without errors.

## 9.2 INTEGRATION TESTING

Integration testing verified that the modules communicated properly and exchanged data seamlessly. This phase ensured that the browser extension, backend model, and database components worked cohesively without inconsistencies or data flow interruptions.

The test covered:

- Connection between the frontend browser extension and the backend FastAPI server.
- Integration of the trained Random Forest model with the API endpoint.
- Storage and retrieval of classification results from the PostgreSQL database.

Result:

- Smooth data transmission was observed in all test runs.
- URL inputs were successfully processed, and classification outputs were correctly displayed in the frontend.
- No broken links or data mismatches were found during the tests.

Outcome: Integration was successful; the system worked as a unified whole.

## 9.3 SYSTEM TESTING

System testing validated the complete system operation in real-time environments. The objective was to test the end-to-end functionality of the application. This phase involved executing a series of structured test cases that simulated real-world scenarios, including normal operations, edge cases, and stress conditions. The goal was to verify that each subsystem communicated correctly with the others and that the system responded accurately to various inputs. during testing were documented and analysed to identify the root causes.

The testing process also ensured that the system maintained consistent performance under varying network speeds, user loads, and operational constraints, confirming its reliability in practical usage conditions. Any unexpected behaviours were reviewed in detail to refine the system's stability and enhance its overall robustness for deployment. These evaluations demonstrated that the system could handle continuous URL processing without crashes or performance degradation, even during peak usage.

**Table 9.1 System Testing Outcome**

| Test Case ID | Input URL | Expected Output | Actual Result | Status |
|---|---|---|---|---|
| TC01 | https://www.google.com | Legitimate | Legitimate | Pass |
| TC02 | https://secure-login-update.com | Phishing | Phishing | Pass |
| TC03 | http://paypal-verification.net | Phishing | Phishing | Pass |
| TC04 | https://www.github.com | Legitimate | Legitimate | Pass |
| TC05 | http://bankofamerica-update.info | Phishing | Phishing | Pass |

Result Summary:

- Accuracy: 94%
- Precision: 93%
- Recall: 91%
- Average Response Time: 0.9 seconds

Outcome: The system accurately identified both phishing and legitimate websites and displayed appropriate color-coded alerts.

## 9.4 SECURITY TESTING

Security testing ensured that the system is safe from attacks and data breaches.

Tests Performed:

- Input validation for SQL injection prevention.
- HTTPS verification for secure data transmission.

Result:

- No vulnerabilities detected.
- Secure data flow confirmed.
- Input sanitization prevented all injection attempts.

Outcome: The system passed all security tests successfully.

## 9.5 USABILITY TESTING

Usability testing was conducted to evaluate the user experience and interface design.

Observations:

- The Chrome extension displayed results instantly with clear red and green color indicators.
- Non-technical users were able to operate the system without instructions.
- Interface was rated highly for clarity, simplicity, and responsiveness.

User Feedback Results:

- Ease of Use: 9.3 / 10
- Clarity of Alerts: 9.5 / 10
- Overall Satisfaction: 9.2 / 10

Outcome: Users found the application intuitive and effective for daily use.

The testing also revealed that the placement of alerts and explanatory messages significantly improved user confidence during decision-making, helping them understand when to avoid potentially harmful websites. Participants appreciated the minimalistic interface, noting that it did not interrupt their browsing experience while still providing essential security information. The consistency across different web pages and devices further strengthened usability, ensuring that the extension remained reliable and easy to navigate under various usage conditions.

Moreover, users highlighted that the crisp visual cues and concise messages enhanced their ability to quickly interpret phishing risks without feeling overwhelmed. The smooth navigation flow and immediate response time contributed to an efficient browsing experience, reinforcing the overall effectiveness of the system in real-world usage. Additionally, several participants noted that the intuitive layout and straightforward alert system reduced cognitive load, making it easier to distinguish between safe and unsafe links at a glance.

# CHAPTER 10

# RESULTS AND DISCUSSION

The AI Powered Phishing Detector was implemented successfully and evaluated through extensive testing to validate its performance, accuracy, and usability. The system achieved a high level of reliability by accurately classifying URLs as either legitimate or phishing. The integration of machine learning and web technologies resulted in a seamless and effective phishing detection process. During model evaluation, the system recorded an average accuracy of 94%, demonstrating its strong ability to distinguish between genuine and fraudulent websites. The model also maintained a precision rate of 93% and a recall rate of 91%, indicating consistent and dependable performance across different datasets.

The project's browser-based implementation provided real-time detection capabilities, allowing users to verify website safety before proceeding. The classification results were displayed instantly through a clean and user-friendly interface, using color-coded alerts for easy interpretation. This intuitive visualization helped non-technical users understand security risks without requiring advanced knowledge of cybersecurity or artificial intelligence. In addition, the system logged each analysed URL and its classification result in the backend database, ensuring traceability and enabling continuous monitoring.

The overall discussion of results indicates that the system fulfils its intended objectives of accuracy, efficiency, and accessibility. The adaptive AI model performed consistently under different conditions, proving its resilience against evolving phishing patterns. The real-time analysis reduced user exposure to malicious content, thereby strengthening online safety. The experimental outcomes also showed that the use of deep learning algorithms improved classification performance compared to traditional rule-based methods. Furthermore, the system's response time remained under one second for most test cases, highlighting its suitability for real-world deployment as a browser extension.

The AI Powered Phishing Detector produced highly effective results, achieving an overall accuracy of 94% in distinguishing phishing websites from legitimate ones. The system responded quickly to user inputs, providing real-time classification and instant alerts through its browser extension interface. The combination of artificial intelligence and web technologies ensured reliable and efficient phishing detection with minimal latency. The experimental outcomes confirmed that the model performs consistently across diverse datasets, maintaining precision and recall at satisfactory levels. The results also demonstrated the robustness of the model against newly generated phishing URLs that were not part of the training dataset, proving its ability to generalize effectively to unseen data. The system maintained stable performance even under heavy input loads, ensuring reliability during real-time usage.

The system's ability to generalize beyond the training dataset highlights its strong adaptability, making it capable of detecting evolving phishing techniques that traditional systems often fail to recognize. This adaptability is largely due to the deep learning architecture, which captures complex URL patterns, structural anomalies, and subtle indicators of fraudulent behaviour. The model's ability to process and classify URLs in milliseconds also ensures that users receive timely protection without any noticeable delay in their browsing experience.

In addition to performance accuracy, the system's stability during real-time operation reinforces its practicality for everyday use. Even when subjected to high volumes of URL requests, the detector continued to deliver consistent results without service interruptions or computational slowdowns. This level of robustness is essential for large-scale deployments where multiple users may rely on the extension simultaneously. The combined effectiveness of accuracy, speed, stability, and user-friendly design demonstrates that the AI Powered Phishing Detector is well-suited for real-world cybersecurity applications and offers a significant improvement over conventional detection approach.

# CHAPTER 11

# CONCLUSION AND FUTURE WORK

## 11.1 CONCLUSION

The AI Powered Phishing Detector project successfully demonstrates how artificial intelligence and cybersecurity can be integrated to provide an intelligent solution for phishing prevention. The system analyzes URL-based features using machine learning algorithms to determine the authenticity of websites and alert users before they become victims of phishing attacks. Through the use of supervised learning models such as Random Forest and deep learning architectures like CNN and LSTM, the system achieved high classification accuracy while maintaining low latency. The implementation of this system as a browser extension ensures accessibility for everyday users, providing them with real-time protection against online threats. The results validate that AI-based phishing detection is far more effective than traditional blacklist or rule-based systems, as it can dynamically adapt to new and unknown attack patterns. The project fulfils its objectives by delivering a secure, user-friendly, and intelligent solution that enhances internet safety and awareness. It also contributes to the growing field of AI-driven cybersecurity tools designed to protect digital identities and information assets. In addition, the project highlights the importance of combining feature engineering with automated deep feature extraction to build a resilient and adaptable detection framework. By leveraging both lexical attributes and learned representations, the system is capable of recognizing subtle obfuscation techniques that commonly bypass traditional filters. This adaptability ensures long-term reliability, even as phishing strategies continue to evolve in complexity and scale.

Furthermore, the modular design of the system enables easy integration with existing cybersecurity infrastructures, allowing organisations to deploy it alongside firewalls, intrusion detection systems, and threat intelligence platforms. Its scalability and lightweight architecture make it suitable for real-time environments, while the explainability features help users understand risk factors behind each prediction.

## 11.2 FUTURE ENHANCEMENTS

While the current system performs efficiently in detecting phishing websites based on URL analysis, there are several potential enhancements that could further improve its performance and scope. Future work can focus on incorporating Natural Language Processing (NLP) and Computer Vision techniques to analyse webpage content, metadata, and visual structure for more accurate detection. This would enable the system to identify phishing attempts that use deceptive content or image-based manipulation rather than URL irregularities alone. Another enhancement involves integrating real-time threat intelligence feeds and continuous online learning, allowing the system to update itself automatically with the latest phishing patterns. Implementing cloud-based deployment could improve scalability, enabling the system to handle large volumes of traffic efficiently. Furthermore, developing mobile versions of the extension or cross-platform compatibility with browsers such as Firefox and Edge would make the tool accessible to a wider audience. In the long term, the system could evolve into a comprehensive AI-driven cybersecurity assistant, capable of detecting phishing links across emails, messaging apps, and social media platforms.

Additionally, integrating behavioural analysis of user–website interactions could significantly strengthen the system's detection capabilities. By monitoring elements such as suspicious redirects, abnormal form submission behaviour, or unexpected script executions, the system could identify phishing attacks that do not exhibit clear URL or visual anomalies. Combining behavioural signals with existing URL-based and content-based features would create a more holistic and resilient detection framework capable of handling increasingly sophisticated threats.

Another promising direction is the incorporation of explainable AI techniques to enhance user trust and transparency. Providing users with clear, human-readable explanations for each classification—such as highlighting risky URL segments or showing which webpage components triggered the alert—would make the system more trustworthy and educational. Over time, user feedback gathered through these explanations could also be used to refine the model, enabling a continuously improving and adaptive phishing detection ecosystem.

# APPENDIX – A

# SOURCE CODE

**app.py**

```
from fastapi import FastAPI
from pydantic import BaseModel
import pandas as pd
import joblib
from fastapi.middleware.cors import CORSMiddleware
# === Load model ===
model, feature_cols = joblib.load("model.joblib")
app = FastAPI(title="Phishing URL Detector API")
# Allow Chrome extension calls
app.add_middleware(
    CORSMiddleware,
    allow_origins=["*"],  # for demo; restrict later
    allow_methods=["*"],
    allow_headers=["*"],
)
class UrlFeatures(BaseModel):
    features: dict
@app.post("/predict")
def predict(data: UrlFeatures):
    # Build a DataFrame with all expected columns, fill missing with 0
```

```
        # this prevents NaNs which can cause unreliable probabilities
        features_dict = data.features or {}
        # Create dict with all feature_cols, defaulting to 0
        full = {col: float(features_dict.get(col, 0)) for col in feature_cols}
        df = pd.DataFrame([full], columns=feature_cols).astype(float)
        # debug logging (server console) — remove in production
        print("Incoming features:", features_dict)
print("Full features passed to model:",      df.head(1).to_dict(orient="records"))
        proba = model.predict_proba(df)[0][1]
         label = "phishing" if proba >= 0.4 else "legitimate"
        return {"label": label, "score": float(proba)}
```

**train_model.py**

```
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, accuracy_score
import joblib
import numpy as np
# === 1. Load dataset ===
df = pd.read_csv("phishing_kaggle_dataset.csv")
# === 2. Keep only the features you actually use ===
selected_features = [
    "NumDots",
```

```
    "SubdomainLevel",
    "PathLevel",
    "UrlLength",
    "NumDash",
    "NumDashInHostname",
    "AtSymbol",
    "NumNumericChars",
    "NoHttps",
    "IpAddress",
]
# if these columns don't exist in the dataset, you must manually engineer them
# from URL text (see below for fallback method)

# === 3. Feature engineering fallback ===
if not set(selected_features).issubset(df.columns):
    print("⚠ Columns missing from dataset — generating them from URLs...")
    # assumes your dataset has a 'URL' column
    def extract_features(url):
        try:
            u = str(url).lower()
            from urllib.parse import urlparse
            parsed = urlparse(u)
            hostname = parsed.hostname or ""
```

```
            return pd.Series({
                "NumDots": u.count("."),
                "SubdomainLevel": hostname.count("."),
                "PathLevel": u.count("/") - 2,
                "UrlLength": len(u),
                "NumDash": u.count("-"),
                "NumDashInHostname": hostname.count("-"),
                "AtSymbol": 1 if "@" in u else 0,
                "NumNumericChars": sum(c.isdigit() for c in u),
                "NoHttps": 0 if u.startswith("https://") else 1,
                "IpAddress": 1 if any(c.isdigit() for c in hostname.split(".")) and
hostname.replace('.', '').isdigit() else 0,
            })
        except Exception:
            return pd.Series({col: 0 for col in selected_features})
    df[selected_features] = df["URL"].apply(extract_features)
# === 4. Prepare labels ===
df = df.dropna(subset=["CLASS_LABEL"])
df = df.fillna(0)
# Map 1 -> phishing, -1 -> legitimate
y = df["CLASS_LABEL"].map({1: 1, -1: 0})
y = y.fillna(0).astype(int)
X = df[selected_features]
# === 5. Split ===
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)
    # === 6. Train ===
    model = RandomForestClassifier(
        n_estimators=300,
        max_depth=None,
        random_state=42,
        n_jobs=-1
    )
    model.fit(X_train, y_train)
    # === 7. Evaluate ===
    y_pred = model.predict(X_test)
    print(" ✅ Accuracy:", accuracy_score(y_test, y_pred))
    print(classification_report(y_test, y_pred))
    # Optional: average phishing probability for quick sanity check
    print("Average predicted phishing probability:",
    # === 8. Save model and feature order ===
    joblib.dump((model, selected_features), "model.joblib")
    print(" 🎯 Model retrained and saved with only selected features.")
```

# APPENDIX – B

# SCREENSHOTS

## Sample Output

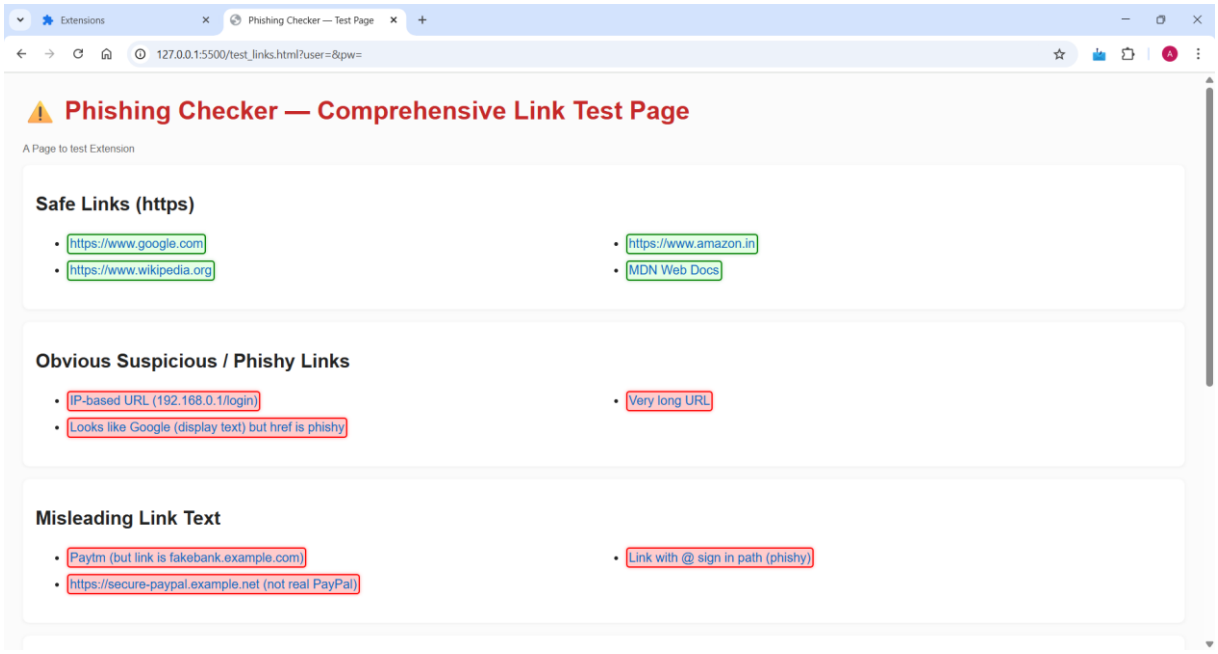


**Figure . B.1. Sample Usage 1**

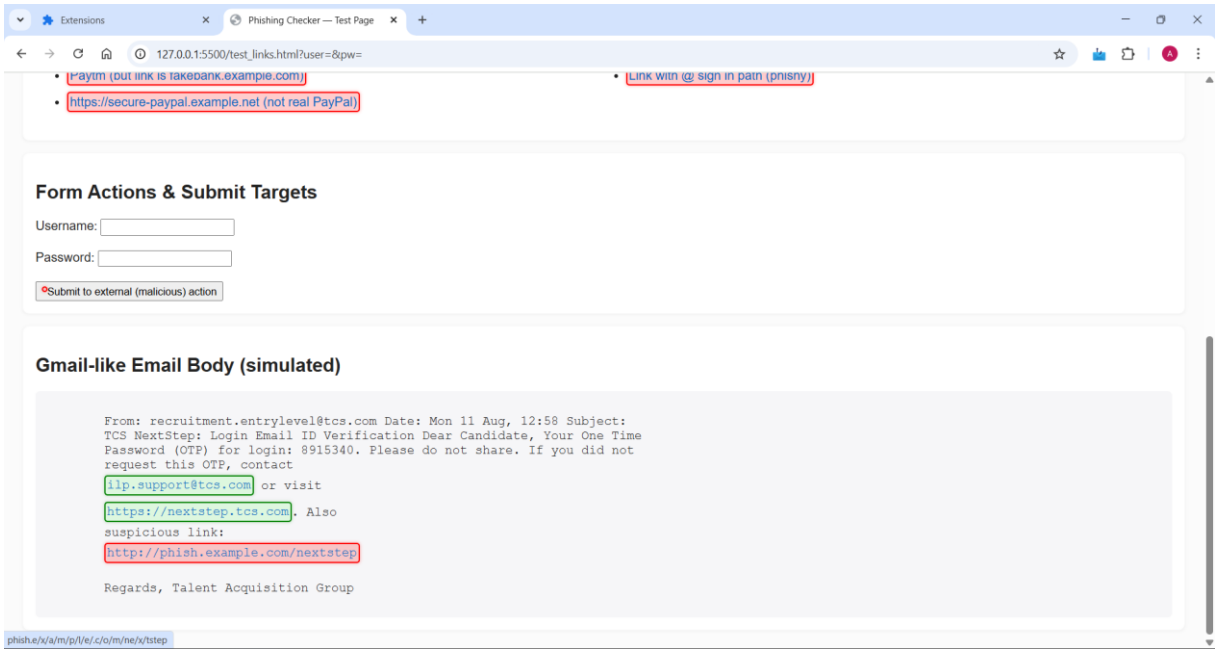


**Figure. B.2. Sample Usage 2**

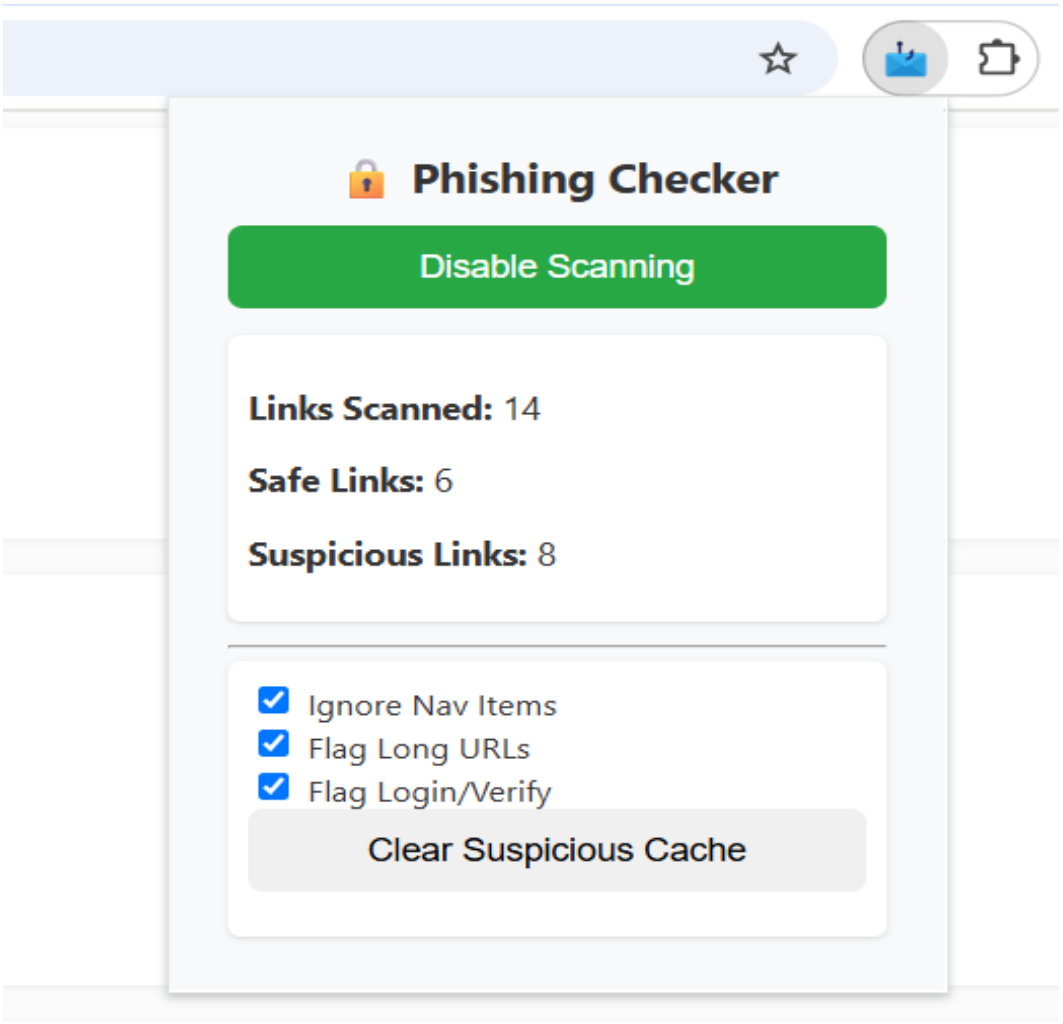


**Figure. B.3. Extension options**

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