**U****RL ANALYZER FOR MALWARE AND VULNERABILITY DETECTION**

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**DECLARATION**

The work mentioned in this document to accomplish the project was carried by us under the supervision of “**Dr. Khurram Zeeshan Haider**” Center of Data Science Government College University Faisalabad.

We hereby declare that the “URLs analyzer for malware and vulnerability detection” and all the contents of this project are the outputs of our efforts and Research. We further declare that the all the work which we mentioned in this document has not been submitted for the award of any other degree or diploma. The university may take action if the information provided in this document is inaccurate at any stage.

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**ABSTRACT**

This report discusses the development of a tool that can analyze URLs to detect malware, viruses, and vulnerabilities using machine learning (ML) and cybersecurity techniques. In today’s digital age, cybersecurity threats like phishing, malware, and hacking have become increasingly prevalent, especially through malicious URLs. This tool is designed to automatically evaluate URLs to identify these threats, providing an effective solution for real-time security. This report covers the tool’s design, implementation, and testing process, `explaining the methodologies and technologies applied to develop an efficient solution for identifying harmful URLs.

**Keywords:** Phishing Detection, Malicious URLs, Random Forest, Machine Learning, URL Feature Extraction, Cybersecurity, Flask API, VirusTotal Integration, Web Security, Threat Intelligence, React Frontend, Binary Classification

# CHAPTER 1: INTRODUCTION

In today's digital age, phishing attacks have become a widespread and dangerous threat. They often begin with a seemingly innocent URL that leads users to malicious websites designed to steal sensitive data such as login credentials, financial information, or personal identity details. As these attacks grow more sophisticated employing obfuscation techniques, spoofed domains, and deceptive content it becomes increasingly difficult for users and traditional security systems to detect them in time.

To combat this evolving threat landscape, SafeScan.Pro was developed as a powerful, real-time phishing detection system that intelligently analyzes URLs and provides actionable insights. Leveraging machine learning algorithms, heuristic analysis, and real-time threat intelligence from external sources like VirusTotal and urlscan.io, SafeScan.Pro can assess a URL's legitimacy within seconds. The system evaluates a variety of features including domain age, URL length, use of HTTPS, presence of suspicious patterns, and top-level domain credibility to generate a comprehensive risk report.

SafeScan.Pro is designed to serve both individuals and organizations, helping them proactively detect and avoid phishing threats before any harm is done. With an intuitive interface, seamless integration capabilities, and continuously updated threat models, it empowers users to make informed decisions about the links they encounter daily ultimately enhancing online safety and digital trust.

## 1.1 Background

In today’s digital age, the internet is an essential tool for communication, business, education, and everyday tasks but it also serves as a growing platform for cybercrime. Among the most common and dangerous threats are phishing attacks, where cybercriminals trick users into clicking on fraudulent URLs that mimic legitimate websites to steal sensitive information, spread malware, or gain unauthorized access. Traditional security methods, such as blacklist-based URL filtering, are no longer effective on their own, as attackers constantly generate new, obfuscated, and zero-day phishing links that bypass static defenses. This gap highlights the need for intelligent, real-time detection systems that go beyond basic rule-matching. To address this issue, SafeScan.Pro was developed as a hybrid, intelligent URL analysis system that leverages machine learning techniques, particularly a Random Forest classifier, to detect suspicious patterns based on lexical and structural URL features. These include indicators such as URL length, subdomain count, use of HTTPS, presence of digits or special characters, and obfuscation patterns. Furthermore, SafeScan.Pro integrates the VirusTotal API to validate results against a global database of known threats, improving the system’s accuracy and reducing the risk of false negatives. With a user-friendly React.js frontend and a lightweight Flask backend, the system enables users to input any URL and instantly receive a clear, reliable safety assessment. SafeScan.Pro thus provides an effective and practical solution to modern phishing threats by combining automation, intelligence, and real-time protection into one accessible platform.

Traditional URL protection methods, such as blacklists and manual filtering, are no longer sufficient in today’s threat landscape. Blacklist-based systems can only detect known threats and fail to recognize newly created, obfuscated, or zero-day phishing URLs. Attackers often craft links that look very similar to legitimate websites by manipulating domain names, adding misleading subdomains, or using shortened URLs. These tactics easily bypass static detection techniques. Moreover, non-technical users typically lack the awareness or tools to verify whether a URL is safe, making them highly vulnerable to social engineering and phishing schemes.

To address these limitations, SafeScan.Pro was developed as a smart and real-time phishing URL detection system. The project utilizes machine learning, specifically a Random Forest classifier, to analyze URLs based on various lexical and structural features. These include URL length, subdomain count, the presence of digits, special characters, HTTPS usage, and suspicious keywords. The model is trained on a large dataset of both benign and phishing URLs, allowing it to learn patterns that indicate whether a link is potentially harmful. In addition to the ML model, the system integrates the VirusTotal API, which checks the URL against over 70 antivirus engines and blacklists, providing an extra layer of verification and improving the system’s overall accuracy.

The SafeScan.Pro platform is designed for usability and performance. It features a modern, responsive React.js frontend that allows users to easily input a URL and receive a fast, clear result. The Flask-based Python backend handles all processing, including feature extraction, model prediction, and VirusTotal integration. The system is capable of delivering real-time analysis and results, making it practical for everyday users, students, and organizations alike. By combining automation, intelligence, and external threat validation, SafeScan.Pro provides a powerful and accessible tool to combat the increasing threat of phishing and protect users in today’s digital environment.

## 1.2 Objectives and Purpose of the Documentation

**SafeScan.Pro** is an advanced full-stack application that detects phishing URLs using a combination of:

**Machine Learning (ML)**: A Random Forest Classifier trained on a curated dataset of malicious and benign URLs.

**Real-time Feature Extraction**: The system extracts a variety of syntactic and statistical features from the input URL.

**External Threat Intelligence**: Integration with the VirusTotal API enhances its detection capabilities using data from global antivirus vendors and blacklists.

**Interactive Web Interface**: A user-friendly React.js frontend allows users to submit URLs and view comprehensive analysis results.

Phishing detection is critical for individuals, organizations, and cybersecurity platforms. Traditional blacklist-based detection systems fail to catch newly crafted or obfuscated malicious URLs. SafeScan.Pro addresses this limitation through:

**Predictive modeling** that generalizes to unseen URLs.

**Explainability**, allowing users to understand why a URL was flagged.

**Hybrid analysis**, blending ML with external databases to ensure broader coverage.

**Purpose of the Documentation**

Developers who want to contribute to or deploy the system, including understanding the codebase, extending features, customizing components, or integrating it into existing security infrastructure.

Students or researchers interested in phishing detection techniques, offering them insights into the end-to-end workflow from data preprocessing and feature extraction to model training, evaluation, and deployment serving as a practical case study in cybersecurity and machine learning.

Security analysts seeking to understand the backend logic of URL classification, with detailed explanations of how risk is computed, how the model handles real-time URL analysis, and how threat intelligence APIs are integrated to enhance decision-making.

Table 1.1 Key Features at a Glance

|  |  |
| --- | --- |
| **Feature** | **Description** |
| ML-Powered Classification | Uses Random Forest to detect phishing patterns. |
| Real-time URL Analysis | Instantly extracts features and makes predictions. |
| VirusTotal Integration | Leverages third-party threat intelligence for higher accuracy. |
| Intuitive Frontend UI | Clean React-based interface for user interaction and result visualization. |
| Comprehensive Reports | Risk scores, feature insights, and external intelligence in one place. |

## 1.3 Problem Statement

In the digital age, cyberattacks have become more frequent, sophisticated, and damaging. One of the most common attack vectors used by cybercriminals is malicious URLs, which serve as gateways to phishing websites, malware, ransomware, and data theft. Phishing attacks in particular exploit human trust, mimicking legitimate websites to trick users into sharing sensitive information such as login credentials or financial details. These attacks are not only affecting individuals but also causing major breaches in organizations worldwide. The growing volume of such attacks highlights the need for an intelligent, automated system capable of detecting and preventing malicious URLs before damage occurs.

Most traditional security systems rely on blacklist-based approaches, where known malicious URLs are stored and blocked. While useful to some extent, these systems have major limitations they cannot detect newly generated, disguised, or zero-day phishing links. Attackers often register domains with slight typos (e.g., g00gle.com), use URL shorteners, or embed harmful content behind long, complex URLs to bypass detection. These obfuscation tactics render blacklists nearly ineffective in real-time threat scenarios. Moreover, static systems offer no insights into why a URL is considered dangerous, leaving users unaware and unprepared to handle future threats.

Additionally, many existing phishing detection tools are either too complex for general users or lack real-time performance. Manual checking is time-consuming and inconsistent, especially when dealing with a large volume of links. On the other hand, machine learning models that do exist often work as isolated components with no integration into real-world web applications. Furthermore, they usually do not validate predictions against external global threat databases, which increases the risk of false positives and false negatives both of which can lead to serious consequences.

Therefore, there is a clear and pressing need for a real-time, intelligent phishing detection system that combines machine learning with external threat intelligence. The system should not only be technically robust but also user-friendly, so even non-technical users can benefit from it. Our project, SafeScan.Pro, aims to fill this gap by offering a hybrid solution that detects and explains malicious URLs using a trained Random Forest classifier and validates results using the VirusTotal API. By addressing the limitations of traditional systems, SafeScan.Pro provides a smarter and safer way to handle URL-based threats.

## 1.4 Project Significance

**SafeScan.Pro** directly addresses a critical and escalating cybersecurity challenge: the rise of highly sophisticated phishing attacks that increasingly evade traditional detection methods. In a digital era where online platforms are integral to communication, commerce, and education, the risk posed by deceptive URLs is more severe than ever.

### 1.4.1 The Growing Threat of Phishing

Phishing attacks have evolved beyond simple imitation tactics. Today’s malicious URLs are often:

* **Well-crafted and obfuscated**, using URL shortening, encoding, or visual tricks to appear legitimate.
* **Dynamic in behavior**, changing appearance or redirection paths to avoid static, rule-based detection.
* **Targeted**, exploiting user psychology and popular platforms to increase click-through success.

These characteristics allow phishing URLs to bypass many signature-based security systems that rely on known blacklists or static patterns. As a result, both everyday users and enterprise systems are increasingly vulnerable.

### 1.4.2 SafeScan.Pro: A Modern Response

**SafeScan.Pro** offers a timely and intelligent solution by leveraging a multi-layered approach that combines:

* **Machine Learning**: For detecting patterns in URLs that are statistically associated with phishing behavior.
* **Heuristic Rules**: To catch suspicious traits like excessive subdomains or unusual character ratios.
* **Global Threat Intelligence**: Through optional external APIs to cross-check real-time threat data.

This layered defense ensures improved accuracy and adaptability compared to traditional URL filters.

### 1.4.3 Accessibility and Practical Value

A key strength of SafeScan.Pro is its **accessibility**. Unlike many enterprise-grade cybersecurity solutions, it does not require advanced technical knowledge or complex installation. Instead, it provides:

* A **lightweight, web-based interface** accessible from any browser.
* **Real-time URL analysis** with near-instant feedback.
* Compatibility across platforms and devices without additional software dependencies.

This design empowers not only tech-savvy users but also **general users, students, educators, and small organizations** offering them a practical tool for cybersecurity awareness and protection.

### 1.4.4 Educational and Community Impact

Beyond its technical capabilities, SafeScan.Pro serves an **educational purpose**. It helps users understand:

* How phishing URLs are structured.
* What traits make a URL suspicious.
* Why certain URLs are flagged and others are not.

By making these insights visible and interactive, the platform promotes cybersecurity awareness and encourages more informed online behavior especially valuable in academic or training environments.

## 1.5 Challenges

Developing an effective phishing detection system like SafeScan.Pro involves addressing several technical and practical challenges. One of the primary difficulties lies in the attackers’ use of evasion techniques. Phishing campaigns frequently use tactics such as URL shortening, character obfuscation, and domain mimicry to bypass traditional filters, making reliable detection increasingly complex.

Another major challenge is sourcing and maintaining high-quality datasets. Since phishing URLs are time-sensitive and often disappear quickly, collecting balanced and up-to-date datasets for training machine learning models is a non-trivial task. Additionally, accurately labeling URLs as “phishing” or “benign” requires consistent verification, often relying on external services or expert analysis.

Feature engineering and model selection also pose significant hurdles. Identifying the most predictive URL-based features, optimizing them for performance, and ensuring the model can generalize well across different types of URLs are all critical components that demand careful consideration. The trade-off between accuracy and real-time processing efficiency further complicates the model design process.

Integrating third-party APIs like VirusTotal introduces limitations such as rate throttling, network latency, and dependency risks. These external tools enhance threat intelligence but can affect the responsiveness and scalability of the system if not managed correctly.

Lastly, creating a user-friendly interface that clearly communicates the risk level of a URL without overwhelming the user requires thoughtful UI/UX design. The system must present technical results in a way that is accessible and actionable for both technical and non-technical users.

## 1.6 Scope of the Project

SafeScan.Pro is a full-stack web application for analyzing the security of URLs, with a focus on detecting phishing, malware, and related web-based threats. The backend is implemented in Python using the Flask framework – a “lightweight and flexible” web micro-framework– while the frontend uses React with Tailwind CSS to build a modern, responsive user interface. The heart of SafeScan.Pro’s analysis is a machine learning pipeline: we train a Random Forest classifier on a labeled dataset of known phishing URLs and legitimate URLs. In training and runtime, the system extracts URL-based features (such as length, subdomain count, presence of suspicious keywords, and other lexical/structural attributes) and feeds them into the model SafeScan.Pro also integrates external threat intelligence: for example, it queries the VirusTotal API when a URL is submitted. VirusTotal’s “Scan URL” endpoint runs the URL through 70+ antivirus engines and blocklists to produce a threat score and context

By combining the Random Forest’s prediction with real-time reputation data from VirusTotal, SafeScan.Pro provides a comprehensive assessment of each URL’s risk. The project is built with modularity and portability in mind. Each component (the Flask backend, the React frontend, the ML analysis module, etc.) is developed as a separate service with clean interfaces. All components are containerized using Docker, so that each service runs in its own isolated environment with its dependencies bundled. In fact, as one Docker tutorial notes, deploying a Flask application in Docker “allows you to replicate the application across different servers with minimal reconfiguration”

## 1.7 Key Features

Machine Learning Detection: SafeScan.Pro employs a Random Forest classifier to distinguish malicious from benign URLs. During development, the classifier is trained on a mixture of labeled phishing and legitimate URLs. As in related research, the model learns from a variety of URL features. The system automatically parses each URL and computes attributes such as length, number of subdomains or directories, the presence of suspicious tokens or keyword patterns, and other lexical/structural characteristics

These features are fed into the Random Forest, which builds an ensemble of decision trees. In practice, when a user submits a URL, SafeScan.Pro extracts the same set of features and obtains a prediction from the trained model: for example, outputting “phishing” or “legitimate” along with a confidence score. Using an ensemble of trees helps improve classification accuracy and generalize well to new URLs. As Ghuge et al. note in a recent study, a Random Forest model “utilizing lexical and structural features extracted from URLs” can effectively detect malicious web links

This ML-based detection provides an automated, data-driven defense against new phishing patterns. Real-time Feature Extraction: SafeScan.Pro is designed to extract URL features on-the-fly as soon as a URL is submitted. The backend includes a feature-extraction module that programmatically breaks down the URL and computes relevant indicators at runtime. For example, it measures the URL length, checks for an IP address in the domain, counts the number of “.” characters (subdomains), and looks for known phishing keywords or scripts. In other words, as one source describes, it extracts “relevant URL features such as length, number of subdomains, [and] presence of specific keywords” This real-time extraction means there is no manual preprocessing step – the moment the URL arrives, the system builds its feature vector. The extracted features are immediately passed to the Random Forest model and to other checks (like VirusTotal). This approach aligns with prior work in phishing detection, which emphasizes on-the-fly analysis of URL lexical and host-based features. By automating feature extraction, SafeScan.Pro ensures fast response times and up-to-date analysis for each scan. VirusTotal Integration: To augment its own analysis, SafeScan.Pro integrates with the VirusTotal service. When a URL is entered, the system can call VirusTotal’s public API (for example, the “Scan URL” or “Get URL report” endpoints). As documented by VirusTotal, their URL scanning service runs the URL through over 70 antivirus engines and blocklists to generate a threat score and context.

# CHAPTER 2: LITERATURE REVIEW

Phishing is a critical and growing cyber threat in the digital world, primarily carried out through deceptive URLs that trick users into believing they are interacting with legitimate websites. These URLs often lead to fake login pages, malware downloads, or forms designed to collect sensitive information. As phishing techniques continue to evolve, conventional protection systems have proven insufficient in offering robust, real-time defenses. This has led researchers to adopt intelligent solutions like machine learning, with a specific emphasis on structured classifiers such as the Random Forest algorithm [1].

### 2.1 Limitations of Traditional Blacklist-Based Systems

Earlier phishing detection systems relied heavily on blacklists databases that stored previously identified malicious URLs. While these methods were once useful, they are highly limited in dynamic threat environments. Cybercriminals now create thousands of unique phishing URLs every day using tactics such as domain spoofing, character substitution (e.g., "g00gle.com"), and URL shortening to bypass filters. Since blacklists can only detect what has already been identified and stored, they fail to detect new, obfuscated, or zero-day phishing URLs, leaving systems exposed [2].

Abutair & Belghith emphasized that blacklists are not scalable in modern contexts. The process of updating and distributing them cannot keep pace with the speed at which new phishing domains are generated and discarded. Moreover, blacklist systems do not provide insight into why a URL is malicious, making them poor tools for learning or user education. These limitations underscore the need for adaptive, pattern-based approaches like machine learning [2].

### 2.2 Rise of Machine Learning in URL-Based Phishing Detection

As phishing attacks became more advanced, researchers began leveraging machine learning (ML) to detect malicious URLs based on patterns instead of fixed rules. ML models can learn from large datasets of labeled URLs and identify complex, nonlinear relationships between input features and phishing behavior. Among various ML techniques, Random Forest has emerged as a preferred solution due to its accuracy, efficiency, robustness, and interpretability, particularly when working with structured data such as URLs [3].

Random Forest is an ensemble learning method that builds multiple decision trees during training and outputs the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. It mitigates overfitting (a common problem with decision trees) by introducing randomness in both data samples and feature selection, which results in a more generalized and stable model [3].

Jain & Gupta demonstrated that a Random Forest model trained on lexical and structural URL features achieved high accuracy in classifying phishing and benign links, outperforming several traditional models. Their research proved that carefully engineered features, when processed by a Random Forest classifier, could effectively capture the differences between phishing and legitimate URLs even in cases where the URLs were carefully disguised [4].

## 2.3 Advantages of Random Forest in Phishing Detection

The Random Forest algorithm offers a unique combination of benefits that make it particularly suitable for phishing URL detection in real-world applications like **SafeScan.Pro**:

* **High Accuracy:** Random Forest is known for producing accurate results, especially in binary classification problems such as phishing vs. benign.
* **Robust to Overfitting:** Due to its ensemble nature, Random Forest reduces overfitting compared to individual decision trees, even on noisy or imbalanced datasets.
* **Fast Inference:** Once trained, the model can make predictions quickly, which is essential for real-time detection.
* **Feature Interpretability:** The model can rank feature importance, helping security analysts and developers understand what drives decisions.
* **Scalability:** It can handle large datasets efficiently and scale well with increasing URL data.

These advantages have led to Random Forest being widely used not only in academic studies but also in deployed systems and open-source phishing detection tools [5].

The following table summarizes key studies relevant to Random Forest-based phishing detection:

Table: 2.1 Work on Random Forest in Phishing Detection

|  |  |  |  |
| --- | --- | --- | --- |
| **Study** | **Model** | **Focus** | **Remarks** |
| Abutair & Belghith (2022) | Blacklist-Based | Traditional detection method | Fails against newly created URLs |
| Jain & Gupta (2021) | Random Forest | Lexical & structural features | High accuracy, stable and interpretable |

These studies form the foundation for projects like SafeScan.Pro, demonstrating that even in a rapidly evolving threat environment, well-structured models like Random Forest can remain highly effective when paired with quality feature extraction and modern APIs [6].

## 2.4 Use Cases and Integration in Real-Time Systems

Random Forest has been integrated into various real-world phishing detection systems due to its balance of speed and accuracy. Many browser extensions, cybersecurity tools, and backend security scanners use tree-based ML models for fast classification of web content and URLs. Its compatibility with frameworks like Flask (used in SafeScan.Pro) allows easy deployment as part of an API service, making it ideal for integration into web applications.

In SafeScan.Pro, the Random Forest model is trained on over 650,000 URLs and exposed through a REST API using Flask. When a user submits a URL, the backend immediately extracts features from the input, processes it through the model, and returns a result phishing or safe in real time. This workflow proves how Random Forest can power practical, efficient, and intelligent cybersecurity applications without requiring complex infrastructure or long processing times [7].

## 2.5 Case Study: Explaining a Single URL Prediction

Consider a concrete example to illustrate the explanation process. Suppose SafeScan.Pro flags the URL http://secure-login.bankexample.com/verify as phishing. The Random Forest model might use features such as “domain contains brand name”, “length of URL”, “has HTTPS (SSL)”, “presence of login keywords”, and “WHOIS domain age”. In this case, the model’s logic could be broken down as follows: (1) the domain uses “bankexample.com” but lacks SSL (i.e. it’s HTTP), raising a red flag; (2) the URL contains a typical login-related word “login” or “verify,” which is often used in spoofing attacks; (3) the domain’s WHOIS data shows it was registered only 2 weeks ago (new domains are a common phishing tactic). SafeScan.Pro would compute how each of these features contributed to the final prediction. For instance, it might assign a high positive weight to “uses untrusted protocol (HTTP)” and “new domain age,” pushing the URL into the phishing class [6].

In the UI, this breakdown could be shown in a step-by-step explanation panel. A possible design is a card titled “Prediction Rationale” listing the top factors: e.g.,

Unsecured Connection (HTTP) – increased phishing score by 0.8.

Newly Registered Domain – increased score by 0.6.

Contains “verify” Keyword – increased score by 0.4.

Accompanying text might say: “This URL was classified as phishing mainly because it lacks HTTPS, is from a newly created domain, and contains a common phishing keyword. Each of these factors contributed to the final score.” This mirrors what a local explanation method does: for example, LIME would perturb the URL features around this instance and fit a simple model to identify which feature changes most alter the prediction. In effect, the system is performing instance-level interpretability: it shows why this particular URL was flagged, rather than just giving a generic model summary. Such a case study illustrates that even though the underlying Random Forest is complex, its decision can be translated into an intuitive explanation by attributing the outcome to concrete URL attributes [8].

## 2.6 Enhancing User Trust and Awareness

Transparent, explainable results have a direct positive effect on user confidence. When SafeScan.Pro not only flags a threat but also clearly shows *why*, users are more likely to trust the system, heed the warning, and take appropriate action. This visibility into the decision-making process reassures users that the alert is not arbitrary it is rooted in observable, logical indicators. Trust is crucial, especially in cybersecurity, where false positives or unclear warnings can lead users to ignore potentially dangerous threats [9].

**Role of XAI in Phishing Detection**

Studies in cybersecurity-focused Explainable AI (XAI) consistently demonstrate that providing clear, concise explanations enhances both user trust and overall system usability. Research highlights that model integrating XAI “offer both high detection accuracy and interpretability,” which ultimately improves system efficiency and user cooperation. By bridging the gap between model prediction and human understanding, XAI transforms abstract outputs into tangible insights users can act on [10].

**Educational Impact: From Black Box to Guide**

If a user can see which characteristics made a URL suspicious such as use of misleading keywords, odd domain age, or non-secure protocol they begin to understand phishing strategies on their own. This shared understanding serves an educational purpose. The machine learning model, rather than being perceived as a black-box oracle, becomes a helpful guide that teaches users how to identify threats themselves. Over time, users become more vigilant and can independently detect risky behavior even outside the system [11].

**Visual and Narrative Explanations**

Industry standards and XAI research agree that the most effective explanations are those that combine visual cues (charts, bars, heatmaps) with narrative reasoning (“This domain is flagged because it uses a suspicious TLD”). SafeScan.Pro can enhance this transparency by highlighting key risk factors like “unusual domain age,” “keyword obfuscation,” or “absence of HTTPS.” Presenting this data in a clear and interpretable format makes the system’s decisions more relatable and trust worthy [12].

**Long-Term Benefits: A Virtuous Cycle**

Explainability doesn’t just fulfill a technical or regulatory checkbox it builds a foundation for long-term success. Informed users who understand the rationale behind alerts are more likely to act responsibly and avoid risky behavior. This feedback loop creates a virtuous cycle: greater trust leads to more frequent usage and deeper engagement with the system, which in turn leads to better-trained users and more accurate outcomes. Over time, SafeScan.Pro doesn’t just protect users it helps them become more security-conscious digital citizens [13].

## 2.7 Feature Importance in Random Forest Classifier

Random Forest classifiers naturally provide a form of interpretability through feature importance scores. In tree ensembles, each split reduces impurity (e.g. Gini index) of the data, and the model can aggregate these reductions to score each feature’s overall contribution. Concretely, scikit-learn’s RandomForestClassifier records the average impurity decrease contributed by each feature across all tree. In practice, this means the model can rank features – such as “contains IP address” or “length of domain name” – by how much they helped distinguish phishing from legitimate URLs. For instance, the chart below illustrates a toy example of feature importances (using mean decrease in impurity, MDI): taller bars indicate features that cause larger drops in impurity, and thus have more influence on the model’s predictions. In the figure, we see that the first three features (0, 1, 2) dominate the model’s decisions, while others contribute only marginally [14].

Although this impurity-based importance is easy to compute (as noted by IBM’s whitepaper: “Random Forest makes it easy to evaluate variable importance”), it has known limitations. In particular, features with many distinct values (high cardinality) can artificially appear more important under MDI. To address this, a complementary measure called permutation importance can be used: it computes how much the model’s accuracy drops when a feature’s values are randomly shuffled. Permutation importance does not bias toward high-cardinality features and can be evaluated on held-out data. The following figure shows the same feature ranking using permutation on the full model, confirming that the same top predictors remain important even when measured by accuracy decrease: the tallest bars again correspond to features 0, 1, and 2. In summary, Random Forests offer both impurity-based and permutation-based feature importance scores, providing insight into which inputs most strongly drive the phishing classifier [15].

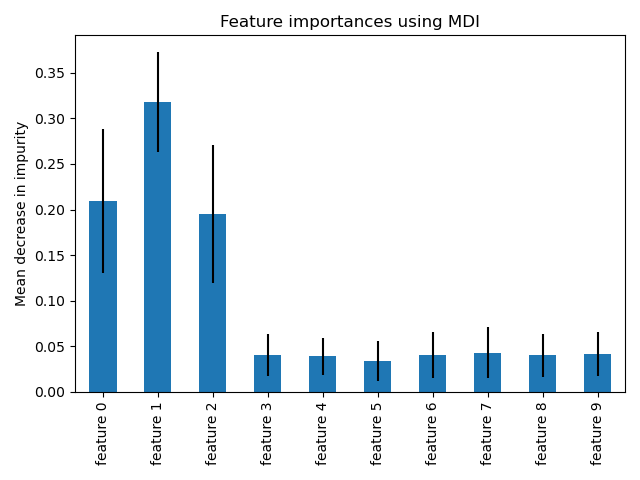


Figure 2.1 Feature Importance Using MDI

Figure 2.1: Example Random Forest feature importance plot (permutation importance). Bars show the mean drop in accuracy when each feature is shuffled, indicating its contribution to correct predictions

# CHAPTER 03: MATERIALS AND METHOD

Phishing attacks have become a widespread and dangerous threat. They often begin with a seemingly innocent URL that leads users to malicious websites designed to steal sensitive data. These attacks exploit human trust and system vulnerabilities to deliver deceptive content, impersonate legitimate brands, or capture personal credentials through social engineering. As phishing tactics continue to evolve employing obfuscated domains, shortened links, and realistic clones of real websites the ability to detect them in real time has become increasingly critical.

The system not only processes each URL through a series of engineered checks but also integrates external intelligence sources such as VirusTotal to enhance its contextual understanding of suspicious domains. With this multi-layered strategy, SafeScan.Pro provides users with actionable insights that go beyond a simple "safe or unsafe" label, offering detailed justification for its predictions. Whether for individual users, educational institutions, or enterprise-level security teams, SafeScan.Pro serves as a vital tool in strengthening online safety and building trust in digital interactions.

This chapter explains the internal architecture and workflow of SafeScan.Pro, focusing on how the system processes a URL to determine whether it is legitimate or a phishing attempt. The process is based on the diagram provided and involves several key components: URL input, feature extraction, dataset construction, machine learning model (Random Forest), and classification output.

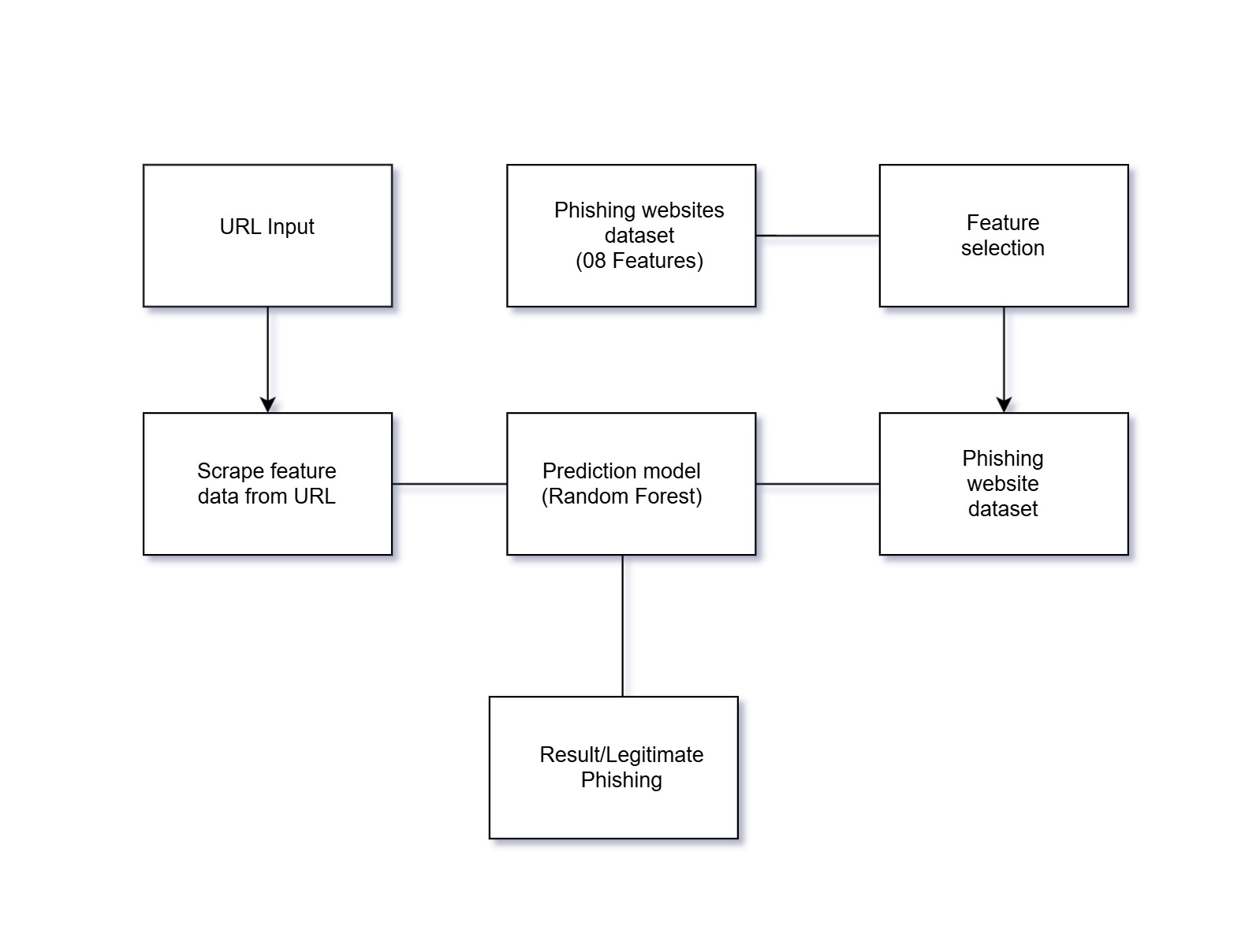


Figure 3.1 Architectural Diagram

## 3.1 Overview of the System

**SafeScan.Pro** is a real-time phishing URL detection system built to intelligently evaluate and classify web links by combining machine learning with meticulously engineered URL features. Its detection pipeline is designed for both accuracy and efficiency, offering quick decisions on whether a URL is legitimate, suspicious, or phishing.

The detection process begins when a user submits a URL through the system’s web interface. This input can be a standard URL, a shortened link, or an obfuscated web address. Once submitted, the system immediately initiates processing to evaluate the nature of the link.

At the core of SafeScan.Pro’s detection pipeline is its feature engineering stage. The system uses a custom extract\_features(url) function to transform the raw string into a structured set of numeric and binary values. These features capture critical indicators such as:

* URL length and character composition
* Number and structure of subdomains
* Use of obfuscation characters like @, //, %
* Top-Level Domain (TLD) legitimacy

This process is optimized for speed and consistency, using regular expressions and parsing libraries to extract over a dozen targeted features in real-time.

### 3.1.1 Phishing Website Dataset

To train the system to recognize phishing URLs, a labeled dataset is used. This dataset consists of thousands of URLs both phishing and legitimate along with associated features.

**Source**: Public datasets (e.g., PhishTank, Alexa), augmented by manually verified entries.

**Kaggle**: [Malicious URLs dataset](https://www.kaggle.com/datasets/sid321axn/malicious-urls-dataset)

**Labeling**: Each URL is tagged as “phishing” or “legitimate.”

**Size**: The dataset should be diverse and frequently updated.

This dataset is the backbone of the training phase, ensuring that the model learns to differentiate based on real-world data.

**Model Prediction: Machine Learning Classification**

Once features are extracted, they are passed to a pre-trained Random Forest Classifier a powerful ensemble-based machine learning model that was trained offline on a labeled phishing dataset. The model evaluates the feature vector and classifies the URL into one of three categories:

* **Benign (Legitimate)**
* **Suspicious**
* **Phishing**

The model’s design allows it to detect both obvious threats and more nuanced patterns that mimic legitimate URLs, providing a high level of precision while maintaining speed.

To improve detection robustness, SafeScan.Pro optionally integrates with **VirusTotal**, an external threat intelligence platform. This step involves securely sending the submitted URL to VirusTotal’s API, which checks its reputation against a collection of over 70 antivirus and cybersecurity engines.

This dual-layer strategy combining predictive classification with real-world verification adds confidence to the results. If VirusTotal flags a URL as malicious, it provides additional evidence that supports or corrects the machine learning model’s judgment.

### 3.1.2 URL Input

The process of detecting phishing or malicious URLs starts with acquiring the target URL from the user. This initial step is critical, as it forms the foundation for all subsequent analysis and predictions carried out by the system. A precise and secure method of accepting and preprocessing the URL ensures the system's reliability and effectiveness.

**Source of Input**

Users can submit URLs through various means, depending on the platform’s design. The system may support:

* **Web Interface**: A user-friendly dashboard where users paste or type in the URL manually.
* **Browser Extensions**: Automatically captures and sends suspicious URLs from a user's active browsing session.
* **API Calls**: External systems or services can integrate and send URLs programmatically for bulk or real-time analysis.
* **Mobile Applications**: In mobile environments, users can submit links from messages, emails, or browsers via an app.

This flexible input design allows for widespread integration into different user environments and usage contexts.

**Types of URLs Supported**

The system is designed to handle a wide variety of URL formats, including:

* **Standard URLs**: Fully qualified domain names (FQDNs) such as https://example.com/login.
* **Shortened URLs**: Services like Bit.ly, TinyURL, etc., often used to disguise malicious destinations.
* **Obfuscated URLs**: URLs with hexadecimal encoding, excessive query parameters, or unusual structures intended to evade detection.
* **Encoded or Encrypted URLs**: Sometimes used in phishing to obscure the actual target.
* **Internationalized Domain Names (IDNs)**: Containing Unicode characters that may mimic trusted domains (IDN homograph attacks).

The system must preprocess and normalize these variations to uncover the actual destination and structure before analysis.

The primary goal at this stage is to capture and store the input URL in a structured format that can be parsed and analyzed effectively. It ensures that the link reaches the backend engine with no loss or alteration of its core components.

Normalize the URL: Ensure consistency by converting the input into a standard format (e.g., lowercase, adding missing protocols).

Validate the URL: Check for malformed or incomplete URLs and reject unsafe or invalid inputs.

Secure Logging: Store the input securely for auditing or model retraining while preserving user privacy.

**Role in the System**

The URL input module **acts as the gateway** to the system’s detection pipeline. It is responsible for:

**Triggering the Detection Process**: Once the URL is submitted, it triggers subsequent steps like feature extraction and classification.

**Ensuring Data Integrity**: Ensures the URL reaches the processing engine without corruption.

**Shielding Against Injection Attacks**: Prevents malicious payloads embedded in the URL input from affecting the system.

**Parsing Integrity**: Misparsed URLs may lead to incorrect feature extraction or false predictions.

**Early Detection of Malformed URLs**: Detecting issues at the input stage reduces downstream errors and resource waste.

**Foundation for Trustworthy Output**: Since all decisions are based on this input, its correctness is non-negotiable.

**Example Scenarios**

1. **A user submits a shortened URL** via the dashboard. The system expands it and then analyzes the final destination.
2. **An API receives a suspicious URL** from a client’s firewall system. It gets automatically sent for analysis without manual intervention.
3. **A mobile app detects a URL** copied from a message. It prompts the user to scan it for potential threats.

The final goal of this scraping process is to convert all identified traits into a **feature vector** a structured list of numerical values that can be fed into a machine learning model.

Here are some examples:

* URLLength: The number of characters in the URL (e.g., 89).
* URLLengthUnsafe: A binary flag (0 or 1) indicating if the URL length exceeds a suspicious threshold.
* NoOfDigitsInURL: Count of digits in the URL (e.g., 12).
* SpacialCharRatioInURL: A float or percentage value showing the ratio of special characters to total characters.
* HasObfuscation: A binary value representing the presence (1) or absence (0) of obfuscation techniques.

Each of these values captures a distinct measurable aspect of the URL, contributing to the system's ability to make an accurate prediction.

**Purpose and Output**

**Purpose**: To translate the raw, human-readable URL into a format that the machine learning model can learn from specifically, a structured dataset where each row represents a URL and each column represents a numerical feature.

**Output**: A **feature vector**, which is a numerical representation of the URL’s characteristics. This vector becomes the input for the next stage in the detection pipeline: **classification**.

## 3.2 Data Collection and Preprocessing

A robust machine learning model is only as good as the data it is trained on. For SafeScan.Pro, training begins with a structured dataset stored in the raw\_data.csv file located inside the backend/data/ directory. This CSV file contains thousands of URL records labeled as **benign**, **phishing**, or potentially other categories depending on the data source.

Preprocessing is a critical step that involves cleaning and structuring this raw data so the machine learning model can make meaningful predictions. Some URLs may be malformed or duplicated; others may contain missing labels or noisy characters. During preprocessing, such entries are removed or corrected.

Additionally, this step may involve:

**Lowercasing** all URLs to ensure uniformity.

**Sanitizing characters** to remove any unwanted whitespace or escape sequences.

**Encoding labels** into numerical values (e.g., phishing = 1, benign = 0) so the model can process them.

By ensuring the input data is well-structured, we allow the learning process to focus on meaningful patterns rather than being distracted by inconsistencies or noise.

## 3.3 Feature Selection

Before training the machine learning model, SafeScan.Pro performs careful feature selection to ensure that only the most relevant URL attributes are used for classification. This step is critical because not all features contribute equally to the task of phishing detection some may introduce noise, redundancy, or unnecessary complexity. By selecting only the most informative features, the system enhances overall model performance, improves generalization, and reduces both overfitting and computational overhead.

Feature selection plays a vital role in improving model accuracy by eliminating irrelevant or weakly correlated attributes that could confuse the learning process. It also reduces the risk of overfitting by focusing the model on core patterns rather than memorizing irrelevant details from the training data. Additionally, with fewer features to process, training time is significantly reduced, making the system more efficient.

To identify the most impactful features, SafeScan.Pro employs several statistical and algorithmic techniques. These include correlation analysis to detect redundant or weakly correlated features, information gain to measure how much each feature contributes to reducing uncertainty in classification, and feature importance rankings derived directly from the Random Forest model. These methods help the system zero in on attributes such as URL length, subdomain depth, special character frequency, and HTTPS presence factors that have been empirically shown to differentiate phishing URLs from legitimate ones. By integrating these techniques, SafeScan.Pro ensures that its model is both streamlined and highly effective.

**Why Feature Selection Matters:**

* Improves model accuracy
* Reduces overfitting
* Lowers training time

SafeScan.Pro uses statistical techniques such as correlation analysis, information gain, and feature importance (from Random Forest) to select the most informative attributes.

**Scrape Feature Data from URL**

After the user submits a URL, the backend system begins the critical task of extracting meaningful data from it. This step transforms a raw, textual URL into a structured and quantifiable format that a machine learning model can process and understand. Since models operate on numerical data not text this transformation is essential for enabling accurate classification.

### 3.3.1 Feature Extraction Process

The system uses a combination of **regular expressions**, **domain parsing libraries**, and **custom heuristic functions** to analyze the URL string. These tools scan and dissect the URL to identify specific traits that are commonly associated with phishing or benign behavior.

This scraping process happens in real time and is designed to handle a variety of URL formats, whether they are standard, obfuscated, or shortened.

### 3.3.2 Types of Extracted Features

The extracted features are chosen based on research and observation of phishing tactics. Some of the key features include:

* **URL Length**: The total number of characters in the URL. Long URLs are often used to hide malicious payloads or mimic legitimate sites.
* **Domain Length**: Shorter domains are often more trustworthy, while unusually long domains may be suspicious.
* **Presence of HTTPS**: Indicates whether the URL uses a secure HTTPS protocol. Although not a definitive sign of safety, the lack of HTTPS can raise red flags.
* **Number of Subdomains**: Many phishing URLs use multiple nested subdomains (e.g., login.secure.paypal.com.phishy.com) to appear legitimate.
* **Number of Digits or Letters**: Excessive numbers or letters in a URL can suggest automatic generation, often associated with malicious campaigns.
* **Special Character Ratio**: Measures how many special characters (like @, -, \_, =, etc.) appear in the URL. A high ratio can indicate obfuscation or an attempt to bypass filters.
* **Obfuscation Flags**: Binary indicators that mark if known tricks are used, such as IP address-based URLs, hexadecimal encoding, or suspicious redirection patterns.
* **Top-Level Domain (TLD) Legitimacy**: Some TLDs (like .tk, .xyz, etc.) are statistically more likely to host phishing content compared to more reputable ones like .com or .org.

## 3.4 Algorithm Flow

### 3.4.1 Random Forest

In your SafeScan.Pro project, the Random Forest isn't just a generic algorithm; it's a specialized "phishing detection expert team" trained precisely on *your* data and your chosen features.

**The Training Phase:**

This is where the Random Forest "learns" from your raw\_data.csv to become an expert.

**Input Data:** The process starts with your raw\_data.csv. Each row in this file represents a url and its type (either 'benign' or 'phishing'). This type column is the correct answer the model needs to learn.

**Feature Transformation (extract\_features):** The core step for the algorithm is transforming each raw URL into numbers. Your extract\_features function is crucial here:

For *every single URL* in raw\_data.csv, it calculates the **11 specific numerical features** (e.g., URLLength, IsHTTPS, NoOfSubDomain, HasObfuscation, TLDLegitimateProb, etc.).

These 11 numbers are what the Random Forest sees and learns from. It doesn't see https://google.com; it sees a set of values like (22, 1, 0, 1, 0, 0, 18, 0, 0.13, 0, 1).

**Creating Diverse "Decision Trees"**

The Random Forest builds a large number (e.g., 100) of individual "decision trees." Think of each tree as a mini-flowchart designed to classify a URL.

**Random Sampling (Bootstrapping):** To make sure each tree is unique, every tree is trained on a *random subset* of the URLs from your raw\_data.csv. This means some URLs from your dataset might be used multiple times for one tree, while others might not be used at all. This "random re-shuffling" makes the trees diverse.

**Random Feature Selection at Splits:** When a tree is deciding how to make its internal "yes/no" splits (e.g., "Is URLLength > 50?"), it doesn't look at all 11 features. Instead, it randomly picks a *smaller group* of your 11 features to consider for that specific split. This forces each tree to learn different rules and prevents them from all focusing on the exact same strongest feature.

**Learning Rules:** Each tree learns a series of rules based on these 11 features and their values, trying to best separate 'benign' URLs from 'phishing' URLs from its random subset of data.

**Saving the Collective Intelligence:** After all these individual trees are built and trained, the entire collection (the "forest") is saved into the random\_forest\_model.pkl file. This file represents the combined knowledge and decision-making capability of your Random Forest expert team.

**The Prediction Phase: Analyzing a New URL in Real-Time**

This is what happens when a user types a URL into SafeScan.Pro.

**User Input:** You provide a new, unknown URL to SafeScan.Pro (e.g., http://example-phish.com).

**Feature Re-Extraction:** Just like in the training phase, your extract\_features function is immediately applied to this *new* URL. It calculates the **exact same 11 features** for this URL. This consistency is absolutely vital for the model to understand the input.

**Individual Tree Votes:** The extracted 11 features of the new URL are then sent to *every single decision tree* within the loaded random\_forest\_model.pkl. Each tree processes these 11 features through its learned rules and makes its own prediction: "I think this is Benign" or "I think this is Phishing," often with a confidence score.

**Majority Voting & Risk Score:** SafeScan.Pro collects all these individual predictions.

**Classification:** The final classification (BENIGN or PHISHING) is determined by the **majority vote** among all the trees. If more trees say "Phishing," that's the final verdict.

**Risk Score:** The "Risk Score" you see (e.g., 87%) is typically derived from the proportion of trees that voted for "Phishing." If 87 out of 100 trees voted "Phishing," the risk score is 87%. This gives you a confidence level in the prediction.

**Why This Is Powerful for SafeScan.Pro:**

**Robustness:** The "wisdom of the crowd" from many diverse trees makes the Random Forest less sensitive to noisy data or outliers in your raw\_data.csv.

**Accuracy:** By combining many predictors, it generally achieves higher accuracy in classifying URLs compared to using just one decision tree.

**Handles Complex Patterns:** It can learn intricate relationships between your 11 features that might not be obvious to a human, allowing it to detect sophisticated phishing patterns.

**Feature Importance (Behind the Scenes):** While not shown to the user, the Random Forest can also internally tell us which of those 11 features were most important for making the final classification, which is valuable for further development.

### 3.4.2 Why Random Forest?

Random Forest is an **ensemble learning method** that builds and aggregates the output of multiple decision trees to make more accurate and generalizable predictions. Unlike a single decision tree that might overfit or misinterpret complex patterns, Random Forest mitigates these risks by combining the "wisdom" of many trees. This collective decision-making process enables the model to capture intricate relationships between features such as subtle obfuscation patterns or irregular token usage in URLs.

### 3.4.3 How the Model Works

The operation of the Random Forest Classifier involves three key steps:

* **Training Phase**; During training, the model generates multiple decision trees. Each tree is trained on a randomly selected subset of the full dataset (using bootstrapping) and considers a random subset of features for splitting nodes. This randomness ensures diversity among trees, which enhances the robustness of the final model.
* **Prediction Phase**: When a new URL is submitted for evaluation, it is passed through each decision tree in the forest. Each tree makes an independent prediction classifying the URL as *benign*, *suspicious*, or *phishing*.
* **Majority Voting**: The final classification is determined by **majority vote**. The label that receives the highest number of votes from all trees becomes the model’s final output. This ensemble technique reduces the impact of misclassification by any single tree and enhances overall accuracy.

Core Advantages of Random Forest

Random Forest brings several strengths that make it well-suited for phishing URL detection:

* **Handles Non-linear and High-dimensional Data**: Phishing datasets often contain noisy or irregular patterns. Random Forest effectively handles such complexity and does not require extensive data preprocessing or transformation.
* **Resilience to Overfitting**: Since the model relies on multiple diverse trees, it avoids overfitting a common challenge in classification tasks, especially with limited or imbalanced data.
* **Feature Importance Ranking**: One of the most valuable aspects of Random Forest is its ability to evaluate and rank the importance of features. This insight allows SafeScan.Pro to understand which URL attributes such as domain depth, character ratios, or obfuscation flags have the greatest influence on prediction outcomes. This enhances both **explainability** and **model optimization**.

**Offline Training and Real-time Prediction**

To ensure high performance and minimal latency, the model is **trained offline** using a comprehensive, labeled dataset of phishing and non-phishing URLs. Once training is complete, the model is serialized and deployed in memory, enabling **real-time predictions** without retraining.

This approach offers several practical benefits:

* Rapid response times
* Efficient resource usage
* Easy updates as new data becomes available

**Summary of Model Workflow**

* **Training**: Multiple decision trees are trained on random data subsets.
* **Prediction**: Each tree evaluates the input URL independently.
* **Decision**: Results are aggregated via majority voting for a final label.

## 3.5 Key Functional Modules

The SafeScan.Pro system is architecturally divided into distinct functional modules, each responsible for a specific aspect of the URL analysis pipeline. These modules work together to deliver accurate, real-time phishing detection with a smooth user experience.

### 3.5.1 Machine Learning Module:

At the core of the detection system is a machine learning module powered by a Random Forest Classifier. This model is trained on a labeled dataset consisting of both benign and phishing URLs. When a new URL is submitted, the system extracts relevant features and feeds them into the classifier. The model then outputs a classification typically "Benign," "Suspicious," or "Phishing" along with a risk probability score that quantifies the likelihood of the URL being malicious. This probabilistic output not only flags dangerous URLs but also helps in ranking and prioritizing threat levels based on severity. The use of a Random Forest ensures robustness and high accuracy by aggregating the predictions of multiple decision trees.

### 3.5.2 Feature Extraction Module:

This module is responsible for transforming raw URLs into meaningful numerical representations used by the ML model. It employs a combination of heuristic checks and statistical analysis to extract a wide range of features from the submitted URL. These features include URL length, number of digits, presence of HTTPS, count of subdomains, frequency of special characters, and lexical anomalies often associated with phishing attempts. The same set of feature extraction rules is applied during both the model training phase and real-time prediction, ensuring consistency and reliability in results.

### 3.5.3 External Threat Intelligence Integration:

To enhance detection accuracy and cover blind spots in the machine learning model, SafeScan.Pro integrates with the VirusTotal API. When a URL is analyzed, the system queries VirusTotal to check whether the URL appears in its database of known threats, which is aggregated from over 70 antivirus engines and URL scanners. This additional layer of intelligence is particularly useful for identifying zero-day phishing attacks or URLs that the ML model might not confidently classify due to unfamiliar patterns. VirusTotal’s response helps validate or challenge the ML prediction, adding a level of credibility and real-world context to each analysis.

A screenshot of a diagram

Description automatically generated

Figure 3.2 Random Forest working

## 3.6 External Threat Intelligence

In addition to its machine learning capabilities, SafeScan.Pro enhances detection accuracy by integrating external threat intelligence services, notably VirusTotal and urlscan.io. These platforms provide valuable historical, reputational, and behavioral data about URLs, offering insights that go beyond what can be inferred from static features alone. For example, VirusTotal aggregates results from over 70 antivirus engines, while urlscan.io offers detailed behavioral analysis, such as screenshots, redirection chains, and network activity of scanned URLs.

While machine learning provides powerful capabilities for pattern recognition and predictive analysis, it is not without limitations especially in the context of rapidly evolving cybersecurity threats. Static models, trained on historical data, may struggle to detect **zero-day phishing attacks** or **newly reported malicious URLs** that do not exhibit previously seen patterns. To address this, **SafeScan.Pro** integrates with an external **threat intelligence platform VirusTotal** to enhance its real-world effectiveness.

This integration significantly improves the system’s ability to detect edge cases URLs that may not exhibit obvious phishing patterns and zero-day attacks, which are newly emerging threats not yet reflected in the training data. By comparing the ML model’s prediction with real-world threat intelligence, SafeScan.Pro increases both confidence and coverage in its assessments.

However, to maintain system responsiveness and prevent dependency issues, the use of external APIs is carefully managed. Requests are throttled or made conditional to avoid hitting rate limits, which could restrict access, and to minimize latency, ensuring that the user experience remains smooth and responsive. This balanced approach allows SafeScan.Pro to benefit from rich external data while preserving speed, availability, and reliability.

* **VirusTotal**
* **urlscan.io**

VirusTotal is a powerful threat intelligence platform that aggregates data from over 70 antivirus vendors, domain scanners, and URL reputation services to provide comprehensive security analysis. When a URL is submitted for evaluation, it is scanned simultaneously by multiple engines, each offering its own verdict typically classified as Malicious, Suspicious, Harmless, or Undetected. These individual verdicts are then compiled into an aggregated report that reflects a well-rounded view of the URL’s reputation. This report is accessible through the VirusTotal API, allowing applications like SafeScan.Pro to programmatically retrieve and interpret the scan results, offering users a clearer understanding of potential threats based on the consensus of trusted security sources.

Real-time awareness of emerging threats that have just been identified.

Access to global blacklists maintained by security companies and research organizations.

Cross-verification with other detection systems, which could flag a URL based on behavioral or contextual data not present in the feature set.

This means the model may occasionally miss phishing URLs that are either new, cleverly disguised, or known to external threat databases but not included in the training data.

### 3.6.1 Role of VirusTotal Integration

To overcome these blind spots, SafeScan.Pro incorporates **VirusTotal**, a widely trusted multi-engine scanning service that aggregates detection results from **over 70 antivirus vendors and threat intelligence sources**.

* **Real-time blacklist validation**: The system can query VirusTotal to check whether a submitted URL has been previously flagged as malicious or suspicious.
* **Extended coverage beyond URLs**: VirusTotal also analyzes files and domains, enabling SafeScan.Pro to potentially detect harmful resources linked within the URL.
* **Consensus-based threat judgment**: Instead of relying solely on its own prediction, SafeScan.Pro can compare its results against a broad range of industry-leading security engines adding a layer of contextual confidence and reducing the chance of false negatives.

### 3.6.2 Benefits of the Hybrid Approach

This **hybrid detection strategy** combining machine learning with threat intelligence provides several key benefits:

* **Enhanced detection accuracy**, especially for stealthy or newly identified threats.
* **Reduced risk of blind spots**, thanks to external validation.
* **Higher user trust**, as results are aligned with well-established security tools.
* **Adaptive protection**, even as phishing techniques evolve beyond known training data.

### 3.6.3 Integration Flow in SafeScan.Pro

The VirusTotal integration is handled within the backend logic of SafeScan.Pro, specifically in the app.py file. This process complements the machine learning prediction by adding real-time threat intelligence. The full flow unfolds as follows:

The user initiates a scan from the frontend, which sends a POST request containing the URL to the /predict endpoint of the Flask backend.

Once the backend receives the request, it immediately begins local feature extraction and URL classification using the preloaded machine learning model. Simultaneously, a secondary process is initiated to contact VirusTotal.

To perform the VirusTotal scan, the backend (or the frontend in the demo version) encodes the URL in Base64 format, as required by the VirusTotal API, and sends a POST request to: https://www.virustotal.com/api/v3/urls.

Upon receiving the request, VirusTotal responds with a scan\_id or analysis\_id, which uniquely identifies the scan session.

After initiating the scan, the application waits for approximately 15 seconds, then sends a GET request and retrieve the scan results.

If the analysis is complete, VirusTotal returns a breakdown of engine verdicts, including the number of detections classified as malicious, suspicious, harmless, and undetected.

This data is then embedded into the backends’ final JSON response, alongside the local ML prediction and risk score, and sent back to the frontend. This combined result enables SafeScan.Pro to offer both AI-driven insights and real-world threat validation, enhancing user confidence in the system’s verdict.

## 3.7 Workflow Overview

Below is a high-level description of how SafeScan.Pro processes a URL:

A diagram of steps to a procedure

Description automatically generated with medium confidence

Figure 3.3 Workflow

**Deployment & Modularity**

SafeScan.Pro is built on a modular architecture, meaning its core components the frontend interface, backend engine, and machine learning model are developed and operated as independent yet interoperable units. This separation of concerns allows each part of the system to be maintained, updated, and scaled without disrupting the others. Developers can modify the model or change frontend logic without needing to reconfigure the backend, making the system more maintainable and flexible over time.

**Ease of Development and Testing**

One of the key benefits of this architecture is the ability to develop and test components individually. For instance:

* The frontend can be tested using mock API responses, even if the backend is not running.
* The machine learning model can be trained and evaluated in isolation before being deployed.
* The backend can process real API requests and perform VirusTotal scans without requiring a full frontend interface during debugging.

This isolation streamlines development workflows and supports continuous integration or deployment pipelines.

**Flexible Deployment Options**

Because of its modular design, SafeScan.Pro can be easily adapted for a wide range of environments:

* **Local machine setups** allow for fast testing and debugging during development.
* **Docker-based deployment** provides containerization for consistent performance across systems.
* **Cloud-based hosting** enables scalability and accessibility, allowing the system to serve users in real-time across the web.

The architecture supports integration with additional security tools or services, and future expansions such as using Kubernetes or deploying serverless functions can be explored without redesigning the entire system.

**Secure and User-Centric Design**

In addition to its technical structure, SafeScan.Pro ensures that all URL scans are handled securely. Sensitive operations, such as calling external threat intelligence services (like VirusTotal), are performed server-side to protect API keys and ensure controlled access.

On the user end, results are presented through a simple and intuitive frontend interface, designed to provide quick, meaningful feedback. Users receive clear classifications such as “Phishing,” “Suspicious,” or “Benign” alongside optional details that explain how the result was determined. This transparency not only increases user trust but also improves educational value for those unfamiliar with phishing indicators.

**Example Use Cases**

**Educational Tool:**

SafeScan.Pro serves as an excellent demonstration of how machine learning can be applied in the field of cybersecurity. By offering clear insights into feature extraction, model predictions, and threat intelligence integration, it helps students and researchers understand the end-to-end process of detecting phishing and malicious URLs. Its transparent design and modular architecture make it ideal for academic projects, cybersecurity workshops, and ML explainability studies.

**Browser Extension Backend:**

The backend of SafeScan.Pro can be adapted to power a lightweight browser extension that analyzes URLs in real time. When a user clicks or hovers over a link, the plugin can send the URL to SafeScan.Pro’s backend, which quickly returns a classification and risk score. This enables the extension to warn users instantly about suspicious or malicious links, providing real-time protection while browsing.

**Corporate Email Gateway Integration:**

In an enterprise environment, SafeScan.Pro can be integrated with a company’s email gateway to scan URLs embedded in incoming emails. By analyzing links before they reach the end-user, the system can help prevent phishing attacks and data breaches. Its combination of machine learning and VirusTotal reputation checks makes it well-suited for catching sophisticated or newly launched phishing campaigns.

**Personal Use:**

For individual users, SafeScan.Pro offers a simple and effective way to validate suspicious links. With no need for installation, users can simply visit the web interface, paste a URL, and receive an instant security report. This makes it an accessible tool for non-technical users who want peace of mind before clicking on unfamiliar or potentially harmful links.

## 3.8 Understanding the Prerequisites

Before diving into installation, let’s understand why each required tool matters:

**Python 3.8 or higher**: Required for running the Flask backend and for using libraries like Scikit-learn (used for ML modeling) and Pandas (used for feature processing).

**Node.js (18.x or 20.x)**: Node.js allows us to compile and serve the React application. It comes bundled with npm, which is used to install frontend packages.

**Git** (optional): Helps you clone the GitHub repository directly. Alternatively, you can download a ZIP.

**Visual Studio Code (VS Code)**: A popular IDE with integrated terminal and support for both Python and JavaScript projects. You can view both backend and frontend projects in one window.

## 3.9 Backend Implementation

At the heart of SafeScan.Pro is a robust backend developed in Python using the Flask framework. This backend is responsible for processing URLs, extracting meaningful features, classifying them using a trained machine learning model, and optionally validating them against third-party threat intelligence services. The design emphasizes modularity and accuracy, ensuring the system is both maintainable and effective.

The machine learning model used in this system relies on a structured dataset housed in a CSV file. This dataset contains thousands of URL samples labeled as either benign or phishing. Before feeding the data into the model, it undergoes preprocessing, which includes:

* Cleaning malformed entries
* Removing duplicate records
* Standardizing all URLs to lowercase
* Encoding the labels into binary format (e.g., phishing = 1, benign = 0)

These steps ensure the model is trained on clean and consistent data, improving its reliability and accuracy.

The transformation of raw URLs into a format suitable for machine learning is done through a dedicated feature extraction function named extract\_features. This function breaks down each URL into quantifiable attributes such as its length, number of subdomains, the presence of HTTPS, special character ratios, and other structural cues commonly associated with phishing attempts. These features reflect behavioral patterns of malicious links and give the model strong indicators to make decisions. By implementing this function identically in both the training and inference scripts, SafeScan.Pro ensures consistency and avoids prediction discrepancies.

Training is executed through the model\_trainer.py script, which loads the dataset and applies feature extraction. The data is split into training and testing subsets. A Random Forest Classifier is then trained, evaluated using performance metrics like accuracy and confusion matrix, and finally saved as a serialized model file (random\_forest\_model.pkl).

The process is visually summarized below:

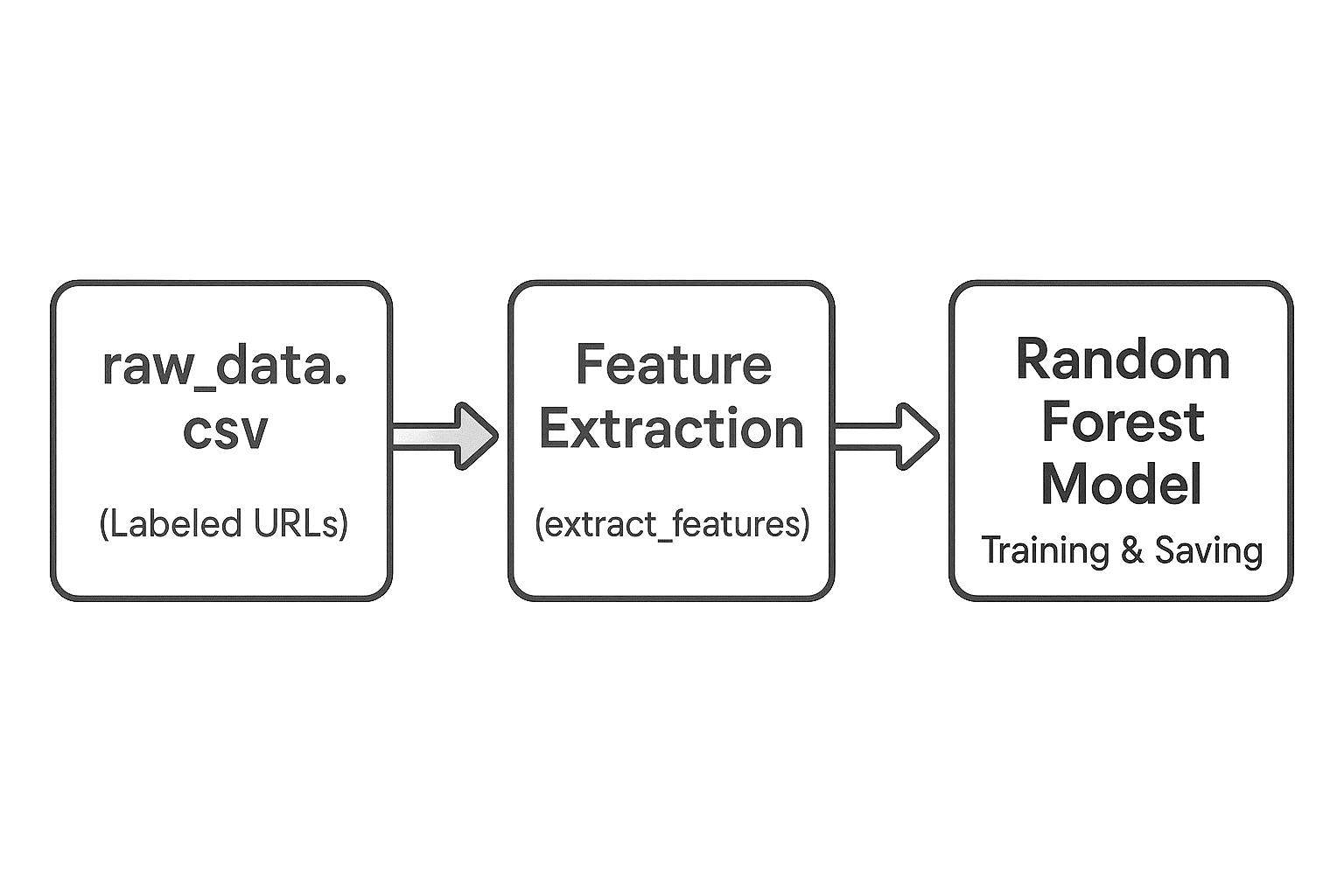


Figure 3.4 Data Pre-Processing

The Flask backend includes a /predict endpoint that accepts JSON payloads with a URL string. Upon receiving a request, it validates the input, extracts feature, formats the data into a compatible structure, and uses the trained model to predict the threat level. Based on the phishing probability score, the URL is categorized into one of three labels:

* **BENIGN**: Less than 30% risk
* **SUSPICIOUS**: Between 30% and 70% risk
* **PHISHING**: Greater than 70% risk

The final output includes a risk score, classification label, feature breakdown, and optionally, results from the VirusTotal API. This JSON response is returned to the frontend for rendering.

To support communication between frontend and backend (which typically run on different ports during development), Cross-Origin Resource Sharing (CORS) is enabled using the Flask-CORS extension. This configuration allows the browser to accept cross-origin requests, mimicking real-world production setups.

The backend is also integrated with the VirusTotal API. If enabled, submitted URLs are sent to VirusTotal, which scans them using multiple antivirus engines. The result, including the number of malicious or suspicious detections, is merged into the final JSON output. This hybrid intelligence enhances detection confidence and reduces false positives.

### 3.9.1 Backend Setup (Flask Application)

The backend is the core computational engine of SafeScan.Pro. It handles all critical processes: taking a URL as input, extracting its features, running predictions using a trained machine learning model, and optionally validating the results via VirusTotal. This section outlines the steps needed to set up and run the backend component of the system.

**Step 1: Navigate into the Backend Directory**

Begin by entering the backend directory, which houses all the essential components for server-side execution: cd backend

This folder contains several key files and subdirectories:

* **app.py** – The main Flask application responsible for handling API requests.
* **model\_trainer.py** – The script used to train the machine learning model.
* **data/** – The directory for storing datasets used during model training.
* **model/** – The folder where the trained model is saved after training.

**Step 2: Set Up a Virtual Environment**

To keep dependencies isolated and avoid conflicts with other Python projects, it is strongly recommended to create a virtual environment:

python -m venv venv

.\venv\Scripts\activate # For Windows

source venv/bin/activate # For macOS/Linux

Activating this environment ensures that all required packages will be installed in an isolated workspace specific to SafeScan.Pro.

**Step 3: Install Required Dependencies**

Install all necessary libraries specified in the requirements.txt file. These include packages for web server handling, machine learning, and data processing:

pip install -r requirements.txt

Some of the core dependencies include:

* **Flask** – For creating RESTful API routes.
* **Flask-CORS** – To allow cross-origin communication between frontend and backend.
* **scikit-learn** – Used for building and using the machine learning model.
* **Pandas & NumPy** – For data handling and numerical operations.
* **Joblib** – To serialize and load the trained model.

If required, you can also configure reverse proxies such as Nginx for production deployment, but this is not mandatory for local development.

**Step 4: Prepare the Dataset**

Ensure that your labeled dataset file, typically named raw\_data.csv, is placed in the following location:

backend/data/raw\_data.csv

This dataset should include URL entries along with labels (e.g., phishing or benign) and is used during the training phase to build the predictive model.

**Step 5: Train the Machine Learning Model**

With the dataset in place, execute the training script to build the model:

python model\_trainer.py

This script performs the following operations:

* Loads and cleans the dataset.
* Extracts a structured set of numerical features from each URL.
* Splits the data into training and testing sets.
* Trains a **Random Forest classifier** on the processed features.
* Saves the trained model as a .pkl file for later use.

Once the script completes, you’ll see confirmation that the model has been saved typically at:

backend/model/random\_forest\_model.pkl

**Step 6: Start the Flask Server**

Finally, start the backend server by running the Flask application:

python app.py

If everything is configured correctly, the server will start without error and begin listening for incoming requests at:

http://127.0.0.1:5000/

Leave this terminal window open, as the backend must remain active to respond to requests from the frontend interface.

## 3.10 Frontend Implementation

The frontend of SafeScan.Pro is developed using React.js and styled with Tailwind CSS. It delivers a responsive, real-time user interface that allows users to submit URLs and view analysis results. The application emphasizes clarity, speed, and transparency.

Frontend logic resides mainly in the App.js file, which manages application state, user input, API calls, and conditional rendering. Supporting files include index.html, which serves as the root HTML, and package.json, which declares dependencies like Tailwind CSS and Lucide-react.

When a user inputs a URL and initiates a scan, a POST request is sent to the Flask backend. While waiting for a response, a loading spinner is displayed to maintain user engagement. Once a response is received, the UI is updated with detailed analysis results.

The interface contains several dynamic sections:

**Static Info Cards**: Displayed by default to educate users about SafeScan.Pro's features.

**Security Analysis Card**: Shows the submitted URL, classification label, risk score, and recommendation.

**Feature Breakdown Card**: Lists the extracted features such as URL length, HTTPS presence, and subdomain count.

**VirusTotal Summary**: If enabled, shows the number of engines that flagged the URL and provides a link to the full report.

The following workflow illustrates the frontend interaction:

User Input → Fetch Request → Backend Processing → JSON Response → Dynamic UI Update

The frontend uses the native JavaScript fetch API and React’s useState and useEffect hooks to manage asynchronous behavior and reactivity. The application can be easily modularized in the future by breaking components into separate functional units such as <UrlInput />, <ResultCard />, and <ThreatInsight />. Further scalability can be achieved by introducing Redux or building authenticated user dashboards.

### 3.10.1 Frontend Setup (React Application)

The frontend allows users to enter URLs, submit them for scanning, and visualize results. It is built with React and styled using Tailwind CSS.

**Step 1: Open a New Terminal**

Don’t close the backend terminal. Open a second terminal and navigate to:

cd frontend

This folder contains:

src/App.js → core logic for UI rendering and API interaction

public/index.html → root HTML file

package.json → defines project dependencies and start scripts

**Step 2: Install Node Modules**

Install necessary dependencies:

npm install

Install icons used in the interface:

npm install lucide-react

**Step 3: Start the React App**

Run the app with:

npm start

This will launch the frontend on:

http://localhost:3000/

**Confirming Successful Setup**

If both backend and frontend are running:

Navigate to: http://localhost:3000/

You should see the SafeScan.Pro interface.

Input a URL and click “Scan”.

Behind the scenes:

The frontend sends your input to the backend.

The backend analyzes the URL and calls VirusTotal.

A full JSON response is sent back and rendered in the UI.

## 3.11 Model Training with Random Forest

The core ML algorithm used in SafeScan.Pro is a Random Forest Classifier, a widely-used ensemble method that combines the outputs of multiple decision trees to improve accuracy and prevent overfitting.

**Why Random Forest?**

**Robustness**: Performs well on unbalanced and noisy datasets.

**Interpretability**: Offers insight into feature importance.

**Scalability**: Can be retrained quickly with new data.

The training process is encapsulated in the script model\_trainer.py. When you run this script, it performs the following steps:

**Loads the dataset**: It reads the raw\_data.csv into a DataFrame and displays basic statistics (e.g., number of samples, label distribution).

**Applies feature extraction**: Each URL is transformed into a set of features using extract\_features.

**Splits the dataset**: Typically, 80% of the data is used for training, and 20% is reserved for validation. This helps to measure model performance on unseen data.

**Fits the model**:

model = RandomForestClassifier (n\_estimators=100, random\_state=42)

model.fit(X\_train, y\_train)

**Evaluates performance**: The script generates a **confusion matrix**, a **classification report**, and an **accuracy score**.

**Saves the model**:The model is serialized using joblib and stored at:

backend/model/random\_forest\_model.pkl

This model file is then loaded into memory by the Flask backend for real-time use.

**Flask API – Powering the Real-Time Predictions**

The Flask application (app.py) serves as the intermediary between the React frontend and the machine learning model. It exposes a RESTful API that allows URLs to be submitted, analyzed, and classified in real-time typically completing the entire process within a few seconds. The key endpoint is /predict, which accepts POST requests containing a JSON object in the format: {"url": "http://example.com/login"}

Upon receiving a request, the Flask backend follows a structured sequence:

**Step 1: Input Validation**

The system first checks whether the request body contains a valid URL string. If the input is missing or incorrectly formatted, the API returns a descriptive error message to the client.

**Step 2: Feature Extraction**

If the input is valid, the URL is passed into the extract\_features function. This function applies a set of heuristics and statistical rules to convert the URL into a dictionary of numerical features relevant for phishing detection.

**Step 3: Data Formatting**

The extracted features are transformed into a Pandas DataFrame and reshaped to align with the format expected by the trained machine learning model. This ensures that the feature order and structure exactly match those used during model training.

**Step 4: Prediction**

The preloaded Random Forest model is used to make a prediction. It returns both a binaryclass (e.g., 0 for benign, 1 for phishing) and a probability score indicating the model’s confidence in its classification.

**Step 5: Risk Scoring and Classification**

The final classification is determined based on the phishing class probability. For instance, probabilities above a defined threshold may be labeled as “Phishing,” while borderline values might be marked “Suspicious.” This risk score is then packaged into a JSON response along with the prediction, allowing the frontend to present a clear and informative result to the user.

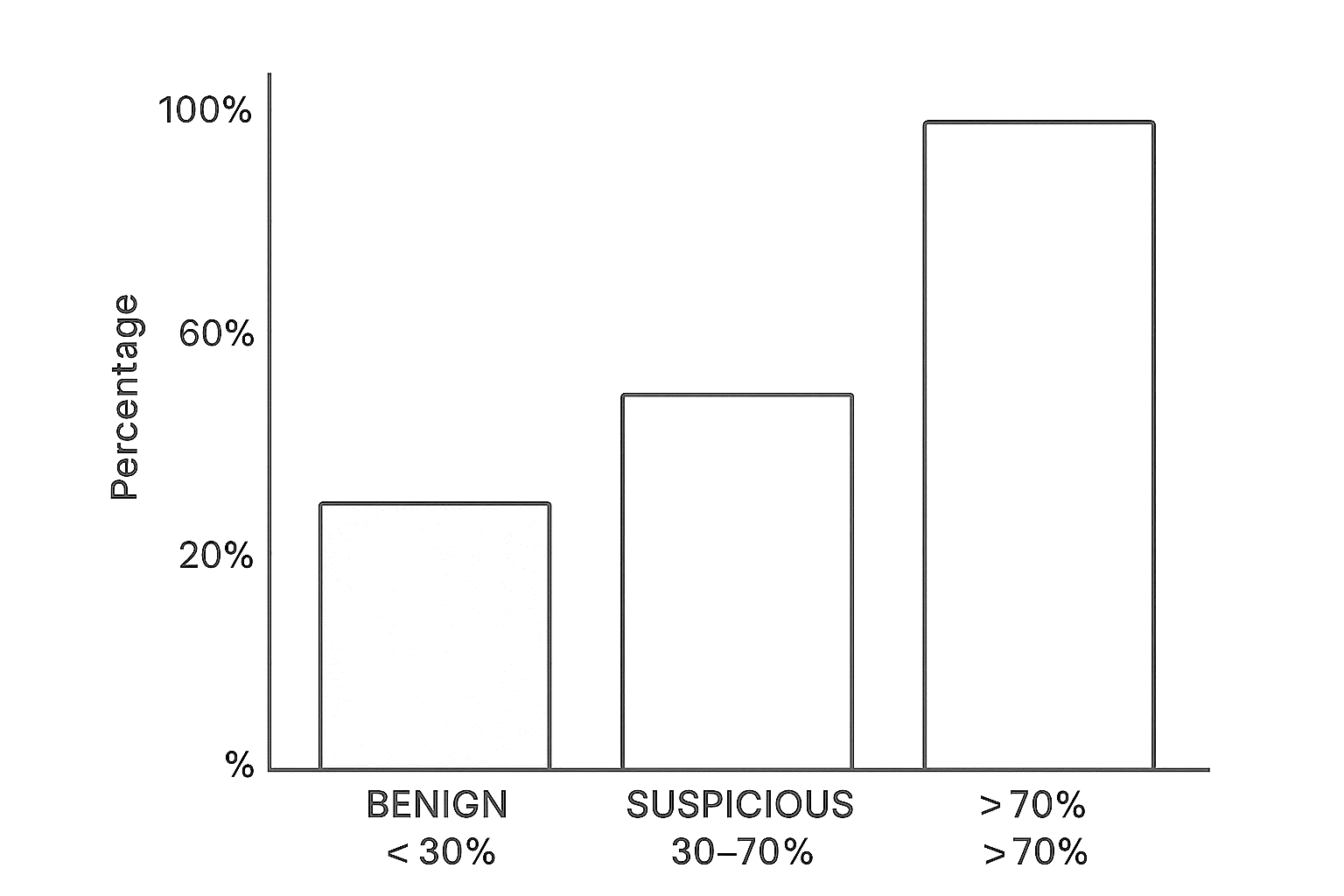
****

Figure 3.5 Risk Scoring Classification

**Step 6: Construct JSON Response**

After completing the prediction and risk scoring, the backend compiles all relevant data into a structured JSON response. This response includes the original input URL, the computed risk score as a percentage, the final classification label (e.g., “Phishing,” “Suspicious,” or “Benign”), and a human-readable breakdown of key features that influenced the decision. Additionally, the response may include a timestamp marking the scan time, a brief summary of the machine learning decision process, and if enabled enriched threat intelligence data retrieved from VirusTotal. This comprehensive JSON response ensures that the frontend can display a detailed and informative result to the user in a clean and transparent format.

## 3.12 UI Components and Sections

Before a user initiates any scan, the interface displays three static informational cards to introduce SafeScan.Pro’s core capabilities. These include:

**Real-time URL Analysis** – Explains that the tool evaluates URLs instantly upon submission.

**ML-Powered Detection** – Highlights that the system uses a trained machine learning model to detect phishing and suspicious patterns.

**Threat Intelligence** – Informs users about the integration with external databases like VirusTotal for enhanced verification.

These cards serve an educational purpose and help set clear expectations about what SafeScan.Pro does. They also contribute to a polished, purposeful default layout that engages users from the start.

### 3.12.1 Security Analysis Card (Post-Scan State)

After a URL is scanned, a dynamic **Security Analysis Card** appears in place of the static info cards. This section presents the key results of the analysis, including:

Analyzed URL – Displays the exact URL submitted for transparency.

Risk Score – Shown as a percentage bar or meter that visually represents the likelihood of the URL being malicious.

Classification – A label indicating whether the URL is considered BENIGN, SUSPICIOUS, or PHISHING.

Recommendation – Simple, actionable advice based on the risk level, such as *“This link appears safe”* or *“Do not click this link.”*

Styling is handled using Tailwind CSS, which applies contextual visual cues based on the classification result:

* Green background for **Benign** URLs
* Yellow for **Suspicious**
* Red for **Phishing**

These colors are intentionally chosen to create an intuitive, emotion-aware interface that reinforces trust and alertness.

### 3.12.2 Feature Breakdown Card

Next to or below the Security Analysis Card, the Feature Breakdown Card provides an in-depth view of the internal decision-making process. This section presents:

Raw feature values – Such as URL length, number of subdomains, digit count, use of HTTPS, and more.

Safety indicators – Each feature is accompanied by a badge or label showing whether it was considered Neutral, Potentially Unsafe, or Highly Suspicious.

This kind of transparency is uncommon in consumer-facing security tools and is one of SafeScan.Pro’s standout features. Rather than offering just a verdict, the tool educates users by showing *why* the model arrived at that decision. This not only builds trust but also makes SafeScan.Pro valuable as a learning platform for users who want to understand phishing patterns and security analysis more deeply.

### 3.12.3 VirusTotal Summary Section

This section is only displayed if the VirusTotal API successfully returns a report. It includes:

Number of malicious, suspicious, and harmless detections

A link to the **full VirusTotal report** online

Status icons or bars for visual clarity

This combination of machine learning and external verification provides **hybrid intelligence** helping confirm or refute predictions from multiple angles.

## 3.13 API Integration (Frontend-to-Backend)

The frontend of SafeScan.Pro communicates with the Flask backend through **HTTP POST** requests using the native fetch API. When a user submits a URL for analysis, the frontend triggers a request to the backends’ /predict endpoint with the following structure:

fetch ("http://127.0.0.1:5000/predict", {

method: "POST",

headers: {

"Content-Type": "application/json"

},

body: JSON.stringify({ url: url })

})

This request sends the input URL in JSON format to the backend, which processes it through the machine learning model and returns a detailed JSON response. Once the frontend receives this response, it parses the data and stores it in a React state variable. This state update automatically causes the relevant React components to re-render, dynamically displaying the updated analysis results to the user in real time.

To ensure seamless communication between the frontend (usually served on port 3000) and the backend (typically on port 5000), Flask-CORS is enabled on the server side. This configuration allows cross-origin requests during development, preventing browser security errors and enabling smooth integration between the two layers of the application.

### 3.13.1 Security Warning: Frontend vs Backend API Calls

In the current prototype of *SafeScan.Pro*, the VirusTotal API key is hardcoded directlyinto the frontend file (App.js). This method was chosen for convenience during early development and demonstration. However, exposing an API key in frontend code is a major security vulnerability. Since all frontend code is accessible to the end user, anyone using a browser's developer tools can view the application’s source code and easily extract the API key. Once exposed, this key can be misused to make unauthorized requests to VirusTotal.

### 3.13.2 Security Implications of Exposed API Keys

Leaving the API key publicly visible introduces serious risks. Malicious users can hijack the key to make excessive or abusive requests to VirusTotal under your quota. This not only drains your usage limits rapidly but may also result in your account being flagged or permanently suspended due to terms-of-service violations. More dangerously, misuse of the API under your credentials could compromise your reputation and trigger unnecessary legal or operational complications. Therefore, protecting the API key is both a technicaland ethical necessity.

### 3.13.3 Moving API Logic to the Backend

To ensure proper security, the API key and any logic involving direct communication with VirusTotal should be migrated to a secure backend server. In this architecture, the frontend never interacts directly with VirusTotal. Instead, it communicates with a backend endpoint such as /api/scan-url through standard HTTP requests. The backend server, in turn, retrieves the API key from environment variables (commonly managed in a .env file) and performs the actual request to the VirusTotal API.

This approach keeps the key completely hidden from users. The frontend receives only the results of the scan such as whether the URL is flagged and what threat engines identified it without any knowledge of how or where the API call was made.

### 3.13.4 Operational Advantages of Backend Handling

Handling VirusTotal requests server-side does more than just hide the API key. It provides **centralized control** over API usage, which allows developers to implement rate limiting, logging, access control, and error handling strategies that are otherwise impossible in a purely client-side approach. If needed, backend logic can also pre-process, sanitize, or enrich user inputs before sending them to VirusTotal, offering a layer of abstraction that helps with maintainability and scalability.

This separation of concerns between the frontend for user interaction and the backend for secure data processing follows industry best practices and ensures the system is prepared for production environments.

### 3.13.5 Scalability, Reliability, and Long-Term Maintainability

Beyond immediate security, migrating the API logic to the backend makes the system more **scalable** and **reliable**. For example, in high-traffic environments, the backend can manage concurrent VirusTotal requests more effectively, cache repeated queries to reduce load, and handle throttling gracefully when API rate limits are approached. Additionally, should the API key need to be rotated or replaced, changes can be made on the server without requiring a full rebuild or redeployment of the frontend code.

This design also opens the door for future enhancements such as integrating additional threat intelligence sources, supporting authentication, or implementing analytics dashboards all while keeping sensitive credentials completely protected.

## 3.14 Error Handling

The integration includes logic to gracefully handle different error scenarios:

Table 3.1 Error Handling

|  |  |
| --- | --- |
| **Scenario** | **Behavior** |
| API Key Missing | Shows a user-facing error message like “API key not found.” |
| Rate Limit Exceeded | Notifies the user to try again later. |
| Invalid URL Format | Skips the scan and returns a warning. |
| Scan Not Completed | Waits up to 15 seconds, then shows partial data. |

The frontend uses conditional rendering to display loading indicators and error messages appropriately, ensuring that the user interface never freezes or breaks.

### 3.14.1 Common Setup Errors & Fixes

Setting up the SafeScan.Pro platform involves multiple components Python, Flask, Node.js, and React working together. During initial configuration or testing, developers may encounter various issues that prevent the system from running correctly. The table below summarizes the most common setup-related errors and provides straightforward solutions.

Table 3.2 Common Setup Errors and Their Solutions

|  |  |  |
| --- | --- | --- |
| **Problem** | **Likely Cause** | **Recommended Solution** |
| Flask server not responding | Virtual environment not activated | Make sure the virtual environment is activated before running app.py. |
| “Failed to fetch” error | Backend server is not running or wrong API URL | Confirm that the Flask server is running at http://127.0.0.1:5000 and accessible. |
| CORS error in browser | Missing Flask-CORS package | Install the flask-cors module and ensure it is added to requirements.txt. |
| React app not compiling | Outdated or incompatible Node.js version | Update Node.js to a compatible version or apply the OpenSSL 3.x workaround if needed. |
| Blank page on frontend | Frontend is not receiving data from backend | Open browser developer tools and check the **Network** tab for failed API responses. |

### 

### 3.14.2 Understanding the Errors

These errors often stem from misconfigured environments, outdated software versions, or missed setup steps. For example, not activating a virtual environment may lead to missing dependencies, while an inactive Flask server will break communication between frontend and backend. Similarly, frontend issues such as a blank screen or failed API calls usually trace back to backend misconfigurations or CORS-related restrictions.

### 3.14.3 Importance of Proactive Debugging

Identifying and resolving these issues early helps avoid wasted development time and ensures smoother testing and deployment. Using browser developer tools (like the Console and Network tabs) and backend logs can significantly speed up the debugging process. Keeping all dependencies updated and consistently using virtual environments also prevents many of these problems.

Table 3.3 Environment Summary

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Layer** | **Language** | **Framework/Tool** | **Main File** | **Port** |
| Backend | Python | Flask | backend/app.py | 5000 |
| Frontend | JavaScript | React, Tailwind | frontend/src/App.js | 3000 |
| ML Model | Python | Scikit-learn | model/random\_forest\_model.pkl | N/A |

SafeScan.Pro is structured across three main layers, each built with specific technologies to ensure functionality, performance, and maintainability. The backend is developed in Python using the Flask framework, with its main logic located in backend/app.py and typically running on port 5000. The frontend is built using JavaScript, leveraging React for dynamic user interfaces and Tailwind CSS for styling, with its entry point at frontend/src/App.js and served on port 3000 during development. The machine learning model, which handles phishing URL detection, is also developed in Python using the Scikit-learn library and is saved as a serialized file named random\_forest\_model.pkl. While the ML model doesn't run on a separate port, it is integrated into the backend for inference during runtime.

## 3.15 Feature Engineering

URLs are fundamentally text strings human-readable, irregular in structure, and highly variable. However, machine learning algorithms require structured numerical data to function effectively. This creates a need for featureengineering, the process of transforming raw data into meaningful inputs that algorithms can interpret.

In the case of SafeScan.Pro, this transformation is performed by a custom-designed function called extract\_features(url). It plays a crucial role in bridging the gap between unstructured input and predictive intelligence.

**What Does the Function Do?**

The extract\_features(url) function takes a single URL as input and returns a **feature vector** a list of numeric and binary values. Each value in this vector quantifies a specific property of the URL that may indicate phishing behavior. These features are derived from empirical observations of phishing strategies and represent a balance of basic structural metrics and behavioral indicators.

The function is handcrafted, meaning it doesn’t rely on pre-trained natural language models or automatic feature generators. Instead, it encodes expert-designed logic that specifically targets the kinds of manipulations phishers often use to deceive users and bypass filters.

### 3.15.1 Why Feature Engineering is Critical

This step is not optional it is fundamental to the system’s success. Machine learning models, particularly structured models like Random Forests, perform best when given features that expose meaningful patterns.

Phishers often rely on certain patterns to trick users. These patterns include:

* **Excessively long URLs** that obscure malicious intent deep within the string.
* **Multiple nested subdomains** that mimic trusted domains (e.g., login.secure.bankofamerica.fake.com).
* **Obfuscating characters** like @, %, //, which can alter how a browser or user interprets a link.
* **Unusual or suspicious Top-Level Domains (TLDs)** such as .xyz, .tk, or .top, which are statistically more likely to host malicious content.

By quantifying these behaviors into measurable attributes, the feature extraction function provides the model with data it can learn from and generalize across new, unseen URLs.

**Where and How It’s Used**

To ensure consistency between training and inference, the extract\_features(url) function is implemented in two key modules:

* **model\_trainer.py**: During the model training phase, this function is applied to every labeled URL in the dataset to generate the features that will train the Random Forest classifier.
* **app.py**: In real-time, when a user submits a URL, the same function is used to convert that input into a feature vector before passing it to the pre-trained model for classification.

Using the exact same feature extraction logic in both stages ensures that the model evaluates live data under the same assumptions it learned during training. This consistency is critical any divergence between training and inference features can lead to incorrect predictions and reduced model reliability.

## 3.16 How It’s Displayed in the UI

### 3.16.1 Threat Intelligence Card (Frontend Rendering)

Once the VirusTotal analysis is complete and the backend response is received, the frontend dynamically renders a **"Threat Intelligence"** card. This component provides users with a visual summary of third-party verdicts, offering an added layer of transparency and verification beyond the machine learning model.

The card displays the following key information:

* **Malicious and Suspicious Detections:** Shows the total number of antivirus engines that flagged the URL as malicious or suspicious.
* **Harmless and Undetected Results:** Indicates how many engines considered the URL safe or did not detect any threat.
* **Direct VirusTotal Link:** A clickable URL that opens the full VirusTotal scan report in a new tab, allowing users to explore detailed results and engine-specific feedback.

To enhance usability and clarity, the component uses **color-coded icons and progress bars** that provide an at-a-glance understanding of the threat level:

* **Red** – Indicates a high-risk result (malicious detections).
* **Yellow** – Signals a moderate threat (suspicious classification).
* **Green** – Denotes safety (harmless or undetected verdicts).

This visual feedback system ensures that even non-technical users can quickly interpret the threat intelligence data and make informed decisions about the safety of the scanned URL.

## 3.17 Benefits of the Hybrid Approach

Combining your local ML model with VirusTotal threat intelligence leads to a more reliable detection system. Each method complements the other:

Table 3.4 Hybrid Intelligence System

|  |  |  |
| --- | --- | --- |
| Model Type | Strength | Weakness |
| Random Forest (Local) | Fast, predictive, offline-capable | May miss new/unseen phishing techniques |
| VirusTotal API (External) | Real-time, global insight, updated daily | Slower, rate-limited, requires connectivity |

Together, the machine learning model and VirusTotal integration form a hybrid intelligence system that significantly enhances the reliability of SafeScan.Pro. This system is capable of detecting previously unseen phishing tactics through pattern recognition, while also validating those predictions against extensive global threat databases. By combining fast, data-driven insights from the ML model with authoritative reputational evidence from VirusTotal, users receive a well-rounded assessment that offers both statistical confidence and real-world verification. This dual-layered approach ensures that threats are not only detected quickly but also backed by trusted security sources for added assurance.

# CHAPTER 04: RESULTS AND EVALUATION

This chapter presents a comprehensive evaluation of the SafeScan.Pro phishing detection system, focusing on both quantitative performance metrics and visual analysis techniques. The goal is to assess how effectively the system distinguishes between benign and phishing URLs using its machine learning model. Key evaluation tools include the confusion matrix, which provides insight into the number of correct and incorrect classifications, and the ROC (Receiver Operating Characteristic) curve, which illustrates the model’s ability to balance true positive and false positive rates across various threshold settings.

Together, these tools help us identify not only the accuracy, precision, recall, and F1-score of the system, but also its behavior under real-world conditions where trade-offs between sensitivity and specificity are crucial. By analyzing these metrics, we gain a deeper understanding of the model’s strengths, its limitations, and potential areas for further optimization or enhancement.

## 4.1 Confusion Matrix Explanation

The **confusion matrix** is a fundamental evaluation tool in classification tasks, providing detailed insight into a model’s prediction performance. Rather than summarizing results in a single accuracy figure, it breaks down predictions into four categories, allowing a deeper understanding of both **correct classifications** and **errors**.

**SafeScan.Pro Confusion Matrix Overview**

For the SafeScan.Pro phishing detection system, the confusion matrix generated from evaluation on the test dataset is as follows:

* **True Positives (TP): 392**: Phishing URLs correctly identified as phishing.
* **True Negatives (TN): 5,510**: Benign URLs correctly identified as benign.
* **False Positives (FP): 69**: Benign URLs mistakenly classified as phishing these represent false alarms.
* **False Negatives (FN): 541**: Phishing URLs incorrectly classified as benign these represent missed threats.

**Interpreting the Results**

This breakdown reveals the **strengths and limitations** of the current model:

* The **true negative count is high**, indicating that the model is particularly effective at recognizing safe, non-malicious URLs. With 5,510 benign URLs correctly classified, users can trust the system to avoid unnecessary warnings in most cases.
* **False positives are relatively low (69 cases)**, which is important in real-world deployment. Excessive false alarms can frustrate users and reduce trust in the system. The current performance reflects well on this front.
* However, the **false negatives (541 cases)** are a more serious concern. These are phishing URLs that the model failed to flag, potentially allowing threats to pass undetected. In cybersecurity, false negatives pose a significant risk because they can lead to users unknowingly interacting with harmful content.

This imbalance between high precision and moderate recall suggests that while the model avoids overreacting to benign URLs, it sometimes underestimates certain types ofphishing attempts possibly those that are more cleverly disguised or fall outside the patterns learned during training.

**Why the Confusion Matrix Matters**

Understanding the confusion matrix is essential for making informed improvements to the model. It highlights specific weaknesses that may not be visible through overall accuracy metrics alone.

For instance:

* If the priority is **minimizing user disruption**, low false positives are desirable.
* If the priority is **maximizing security**, then reducing false negatives becomes critical, even if it slightly increases false positives.

In this context, SafeScan.Pro's confusion matrix suggests that the model may benefit from additional training on **hard-to-detect phishing URLs**, improved feature engineering, or hybrid techniques such as combining machine learning with real-time threat intelligence (e.g., VirusTotal) to catch threats that the model might miss on its own.

## 4.2 How Our System Guessed

The Confusion Matrix is like a report card that shows how many links our system got right and how many it got wrong.

Look at Figure 1 (Confusion Matrix):

"Benign (Actual 0) / Benign (Predicted 0)" (Top-Left, 5510): Our system correctly said 5,510 safe links were safe. This is very good! It means it's great at letting good links pass.

"Benign (Actual 0) / Phishing (Predicted 1)" (Top-Right, 69): Our system mistakenly called 69 safe links "phishing." These are like "false alarms." It's a small number, which is good – it means we don't bother users much with wrong warnings.

"Phishing (Actual 1) / Benign (Predicted 0)" (Bottom-Left, 541): This is where our system missed some threats. It called 541 dangerous "phishing" links "safe." This is a problem, as these dangerous links could get through.

"Phishing (Actual 1) / Phishing (Predicted 1)" (Bottom-Right, 392): Our system correctly found 392 links that were truly "phishing." This is good, but it's less than the number it missed.

What it means: Our system is excellent at knowing a safe link. But it's not perfect at catching *every* dangerous phishing link. This tells us we need more ways to check links, especially for phishing ones.

A blue and white graph

Description automatically generated

Figure 4.1 Confusion Matrix for URL Phishing Detection

**Purpose of the Confusion Matrix**

The **confusion matrix** is a fundamental evaluation tool used to measure the performance of classification models. In the context of SafeScan.Pro, it helps assess how accurately the system distinguishes between **benign** and **phishing** URLs.

It breaks down predictions into four categories:

* **True Positives (TP):** Phishing URLs correctly identified as phishing.
* **True Negatives (TN):** Benign URLs correctly identified as benign.
* **False Positives (FP):** Benign URLs incorrectly labeled as phishing.
* **False Negatives (FN):** Phishing URLs incorrectly labeled as benign.

By analyzing these values, the confusion matrix allows us to compute key performance metrics such as **accuracy**, **precision**, **recall**, and **F1-score**. These metrics offer insights into both the **effectiveness** and **reliability** of the machine learning model. In particular, they help identify trade-offs like whether the model is too aggressive (high false positives) or too lenient (high false negatives) and guide improvements in detection strategies.

## 4.3 Evaluation Metrics

To better understand the model's effectiveness, we derive several standard performance metrics using the confusion matrix values:

* **Accuracy** measures the overall proportion of correct predictions:

Accuracy = (TP + TN) / (TP + TN + FP + FN) = (392 + 5510) / (392 + 5510 + 69 + 541) ≈ 90.29%

This indicates that about 90% of the URLs were classified correctly.

* **Precision** focuses on the quality of phishing predictions:

Precision = TP / (TP + FP) = 392 / (392 + 69) ≈ 85.02%

This means that when the model flags a URL as phishing, it is correct about 85% of the time.

* **Recall (Sensitivity)** assesses how many actual phishing URLs were detected:

Recall = TP / (TP + FN) = 392 / (392 + 541) ≈ 42.01%

This shows a notable limitation: more than half of the phishing URLs were not caught.

* **F1-Score** balances precision and recall into a single metric:

F1 = 2 \* (Precision \* Recall) / (Precision + Recall) ≈ 56.13%

The F1-score reflects the trade-off the model makes between precision and recall. While it's good at avoiding false positives, it's not equally good at detecting all phishing threats.

## 4.4 ROC Curve Analysis

The **Receiver Operating Characteristic (ROC) curve** is a vital performance evaluation tool used to assess the predictive capability of classification models especially in binary and multi-class problems like phishing detection. For **SafeScan.Pro**, the ROC curve provides insights into how well the model distinguishes between phishing and benign URLs at various threshold settings.

**Understanding the ROC Curve**

The ROC curve plots two core metrics:

* **True Positive Rate (TPR)**, also known as **Recall**, on the Y-axis.
* **False Positive Rate (FPR)**, calculated as *(1 - Specificity)*, on the X-axis.

By adjusting the decision threshold for classification (i.e., the cutoff score above which a URL is classified as phishing), the model generates different TPR and FPR pairs, which are then plotted to form the ROC curve.

**SafeScan.Pro's ROC Curve Performance**

For SafeScan.Pro, the ROC curve shows **a strong upward trend toward the top-left corner** of the graph, which is the ideal outcome. This indicates that the model maintains a high true positive rate while keeping false positives relatively low across various thresholds.

**Key performance highlight:**

* **Area Under the Curve (AUC): 0.88**

**Interpreting AUC = 0.88**

The **Area Under the ROC Curve (AUC)** is a single scalar value summarizing the model’s ability to distinguish between classes.

* An **AUC of 0.5** suggests the model has **no discriminative ability** equivalent to random guessing.
* An **AUC of 1.0** indicates **perfect classification** with 100% sensitivity and specificity.
* An **AUC of 0.88**, as achieved by SafeScan.Pro, reflects **excellent discriminatory power**.

In practical terms, this means the model can correctly differentiate between phishing and benign URLs **88% of the time**, regardless of the threshold used. This is a strong result in cybersecurity applications, where the cost of false negatives can be high.

**Why the ROC Curve Matters**

The ROC curve is more than a diagnostic plot it’s a **strategic decision-making tool**:

* In real-world deployments, system administrators or security teams may need to **adjust the classification threshold** based on their priorities:
  + **Higher Recall**: Prioritize catching as many phishing URLs as possible, even at the cost of more false positives.
  + **Higher Precision**: Minimize false alarms to reduce user disruption, even if some phishing links go undetected.
* The ROC curve enables this trade-off analysis by showing how TPR and FPR shift with threshold changes, helping to find the **optimal balance** between security sensitivity and system usability.

## 4.5 Interpretation of Results

The evaluation metrics and visual tools together provide a clear picture of the system's strengths and limitations:

**Strengths:**

High **accuracy** ensures that most predictions are correct.

High **precision** minimizes false positives, which is critical for maintaining trust.

AUC of **0.88** confirms that the model is generally effective across multiple thresholds.

**Weaknesses:**

**Recall is low**, meaning many phishing URLs are missed.

**F1-score is moderate**, suggesting that while the model is good at not flagging safe URLs, it's not as effective in catching all threats.

This reflects a **common trade-off** in security systems: it’s better to miss a few threats than to overwhelm users with false alerts. However, in cybersecurity, missing threats is still a serious issue. Improving recall without sacrificing too much precision is key for future development.

## 4.6 ROC Curve Visualization

To better demonstrate the classification performance of the **SafeScan.Pro** model, a **Receiver Operating Characteristic (ROC) curve** is included as a visual representation. This curve offers a clear, graphical view of how well the system distinguishes between **phishing** and **benign** URLs across varying decision thresholds.

**What the ROC Curve Shows**

The ROC curve plots two key metrics:

* **True Positive Rate (TPR)** – also known as **Recall**, representing the proportion of actual phishing URLs correctly identified by the model.
* **False Positive Rate (FPR)** – indicating the proportion of benign URLs that are incorrectly classified as phishing.

By plotting TPR against FPR at multiple classification thresholds, the ROC curve allows us to assess how the model’s sensitivity and specificity trade off under different conditions.

**Ideal Curve Behavior**

A high-performing model produces a curve that bends sharply toward the **top-left corner** of the graph. This region reflects **high sensitivity** (i.e., catching more phishing URLs) while maintaining **low false positive rates** (i.e., avoiding false alarms).

To complement the visual, we also calculate the **Area Under the Curve (AUC)**:

* An **AUC of 1.0** represents **perfect classification**.
* An **AUC of 0.5** indicates **no discriminative power**, equivalent to random guessing.
* **SafeScan.Pro achieves an AUC of approximately 0.88**, demonstrating **strong overall model performance** and reliable differentiation between legitimate and malicious URLs.

**Why This Matters for Real-World Use**

The ROC curve isn't just a technical artifact it plays a **critical role in model evaluation and deployment decisions**:

* It highlights how well the model balances **false negatives** (missed phishing URLs) and **false positives** (flagging safe links incorrectly).
* It supports **threshold tuning**, enabling system administrators to adjust the model’s sensitivity based on application needs whether to minimize risk or reduce unnecessary warnings.

**Visual Value and Transparency**

Including the ROC curve enhances the interpretability of SafeScan.Pro’s machine learning component. While numerical metrics like accuracy or precision provide snapshots, the ROC curve presents a comprehensive picture of the model’s behavior across all thresholds.

More importantly, it adds transparency to the system, helping stakeholders technical and non-technical alike understand the trade-offs involved and build trust in the tool’s decision-making process.

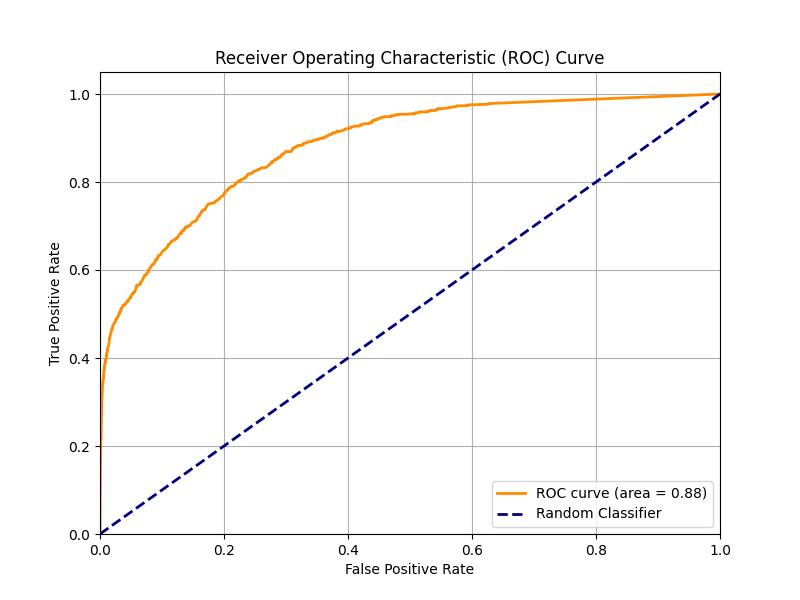


Figure 4.2 ROC curve

The graph demonstrates the model's ability to distinguish phishing URLs from benign ones. The closer the curve is to the top-left corner, the better the model.

* **AUC = 0.88**
* **High sensitivity and specificity**

This curve supports the quantitative metrics and reinforces that the model has strong performance, especially in controlled environments.

## 4.7 Frontend Results

The SafeScan.Pro website is designed to make complex security information easy for you to understand. When you scan a URL, the results are shown in clear sections, helping you quickly decide if a link is safe.

**Security Analysis: Your Main Answer** This is the first thing you'll see, giving you the overall verdict on the URL.

**Analyzed URL:** Shows the exact link you asked SafeScan.Pro to check.

**Risk Score:** This is a percentage (like 87%). It tells you how likely the link is to be dangerous, according to our smart system. A higher number means more risk. This is shown with a colorful bar that visually indicates the risk level from green (low) to red (high).

**Classification:** This is the direct result: "BENIGN" (safe), "SUSPICIOUS" (be careful, some odd things found), or "PHISHING" (very dangerous, avoid at all costs!). Each type has a distinct color so you can instantly recognize the threat level.

**Recommendation:** Based on the classification, you get clear advice, like "This URL appears safe..." or "Exercise extreme caution... Do not proceed."

**Feature Analysis: Why We Think That** This section helps you understand *how* our system came to its conclusion. It breaks down the important characteristics of the URL that our machine learning model looked at.

For each feature (like "HTTPS Security," "URL Length," "Subdomains," "Special Characters," "Domain Length"), you'll see a small detail (e.g., "Secured," "63 characters," "2 detected").

It also gives a simple interpretation (e.g., "Low Risk," "Normal," "Unsecured"). This helps you see the individual "clues" that the system used, like if a link uses secure HTTPS or if it has too many subdomains.

**Confusion Matrix (CM**

The confusion matrix is a table that provides a direct, interpretable breakdown of how well the Random Forest model in SafeScan.Pro is classifying URLs into the correct categories: Phishing or Benign. It’s a great tool for analyzing classification performance in absolute numbers.

When a URL is submitted, the Random Forest model predicts one of the two classes. The confusion matrix captures:

* **True Positives (TP)** – Phishing URLs correctly identified as phishing.
* **True Negatives (TN)** – Benign URLs correctly identified as benign.
* **False Positives (FP)** – Benign URLs incorrectly labeled as phishing (false alarm).
* **False Negatives (FN)** – Phishing URLs missed and labeled as benign (dangerous miss).

**Why it matters in SafeScan.Pro:**

* It shows real-world impact: a high number of FNs means your system is letting dangerous URLs through; a high FP count may lead to user frustration from over-blocking.
* Helps adjust the model or threshold to reduce critical errors.
* Essential for calculating key metrics like accuracy, precision, recall, and F1-score.

**ROC Curve**

The Receiver Operating Characteristic (ROC) Curve is a graphical tool that evaluates the *trade-off between sensitivity and specificity* across different threshold settings. It’s especially useful for understanding the confidence of the predictions made by your model.

SafeScan.Pro doesn’t just say “phishing or not” it also assigns a risk score (like 87%). This allows you to set a threshold (e.g., above 70% = phishing). The ROC curve plots:

* True Positive Rate (Recall) on the Y-axis
* False Positive Rate on the X-axis
* It generates a curve as you vary the decision threshold from 0 to 1.

**Why it matters in SafeScan.Pro:**

* Shows how well the model distinguishes between phishing and benign URLs at all thresholds, not just one.
* The Area Under the Curve (AUC) gives a single value summarizing performance; a value near 1.0 means the model is excellent.
* Useful when you want a flexible security setting e.g., in enterprise use, you might tolerate more FPs to catch more phishing.

Table 4.1 Key Differences at a Glance

|  |  |  |
| --- | --- | --- |
| **Feature** | **Confusion Matrix** | **ROC Curve** |
| **Output Type** | Tabular (TP, FP, TN, FN) | Graphical (TPR vs. FPR) |
| **Focus** | Actual prediction counts | Model’s performance across thresholds |
| **Best For** | Direct evaluation of predictions | Understanding threshold impact |
| **In SafeScan.Pro** | Helps calculate accuracy, recall, precision | Helps assess and tune risk score threshold |
| **Visual Insight** | Simple, discrete numbers | Smooth curve, summary via AUC |
| **Flexibility** | Fixed threshold evaluation | Dynamic threshold exploration |

# CHAPTER 05: SUMMARY

## 5.1 Project Overview and Importance

The project titled SafeScan.Pro addresses the growing concern of phishing and malware attacks delivered through malicious URLs. These attacks deceive users by mimicking legitimate websites to steal sensitive information like passwords, financial data, or personal identity details. Traditional methods like blacklist filters are ineffective in today’s landscape, as attackers rapidly create new, obfuscated links that evade detection. SafeScan.Pro offers a hybrid, intelligent solution that uses machine learning (ML), real-time analysis, and external threat intelligence (such as VirusTotal) to assess and classify URLs as malicious or safe. The tool is especially valuable in a time where both individuals and organizations face heightened cybersecurity threats online.

## 5.2 Objectives and System Goals

The main objective of SafeScan.Pro is to build a full-stack web application that automates the detection of phishing and malicious URLs in real time. The documentation serves multiple audiences, including developers looking to extend the system, students or researchers exploring phishing detection methods, and security analysts seeking explainable, data-driven URL classification. The system uses a Random Forest classifier trained on labeled datasets and extracts structural and lexical URL features such as URL length, number of digits, use of HTTPS, and presence of suspicious tokens. It then combines this with external intelligence from APIs like VirusTotal, ensuring high detection accuracy and broader threat coverage.

## 5.3 Problem Identification and SafeScan.Pro’s Response

Phishing URLs have become harder to detect due to modern techniques like domain spoofing, URL shorteners, and character substitutions. Static detection systems (e.g., blacklists) often fail because they can't predict or detect newly generated URLs. Users especially those with little technical background lack the tools to verify links safely. SafeScan.Pro was developed to solve these issues by providing a smart, real-time detection tool that not only classifies URLs but also explains the reasoning behind its decisions. This makes the system both protective and educational. Unlike other tools, it’s lightweight, easy to deploy, and accessible even to non-technical users.

## 5.4 System Design and Architecture

SafeScan.Pro features a modular architecture, with a Flask-powered backend for logic processing and a React.js frontend for user interaction. URLs submitted by users go through a feature extraction process where characteristics like domain structure, presence of special characters, and keyword usage are analyzed. These features are then passed to a trained Random Forest model for classification. Simultaneously, the system can contact VirusTotal to cross-check the URL against known blacklists and antivirus engines. This dual-layered approach (ML + external intelligence) enhances reliability and reduces false positives or negatives. The backend is designed for performance and scalability, using Docker for containerized deployment.

## 5.5 Dataset, Preprocessing, and ML Model

The backbone of SafeScan.Pro's intelligence is a curated dataset of labeled URLs obtained from sources like Kaggle and PhishTank. Each URL is labeled as phishing or benign and undergoes thorough preprocessing such as cleaning malformed entries, standardizing formats, and encoding labels for ML compatibility. Feature engineering is a key component, where useful metrics are extracted using regular expressions and parsing functions. Features like subdomain depth, digit frequency, HTTPS presence, and TLD credibility are found to be highly predictive. The Random Forest model is chosen for its balance between accuracy, interpretability, and robustness against overfitting, making it ideal for structured URL analysis.

## 5.6 Real-Time Detection and Explainability

SafeScan.Pro provides rapid feedback to users by instantly extracting features and classifying URLs. It includes a scoring mechanism to display the level of risk e.g., "Benign", "Suspicious", or "Phishing" along with a confidence percentage. What sets it apart is its explainability: the system reveals which features influenced the decision most, such as “unsecured HTTP protocol” or “domain registered recently.” This transparency not only increases user trust but also provides an educational element. Users begin to understand phishing patterns and become better equipped to identify risky URLs even outside the platform. Explainability is achieved using both feature importance scores from the Random Forest and visual cues in the frontend.

## 5.7 Integration with VirusTotal and System Workflow

A standout feature of SafeScan.Pro is its integration with VirusTotal, which provides another layer of validation by scanning the submitted URL through more than 70 security engines. When a user inputs a URL, the backend performs both internal ML-based prediction and sends an API request to VirusTotal for verification. The final result is a combination of both, giving users a holistic view of the URL's safety status. The system’s architecture supports API throttling and secure API key management to maintain performance. The frontend UI displays a summary of the analysis, including the number of detections by VirusTotal, further boosting the tool’s credibility.

## 5.8 Future Scope, Applications, and Impact

The project outlines several future enhancements, such as automated retraining of the ML model, better UI customization, dark/light mode support, user authentication, and deployment through Docker and cloud platforms. Use cases range from personal link checking to email security integration and browser plugin support. Additionally, SafeScan.Pro can be integrated into enterprise email gateways to pre-screen links or adapted for use in cybersecurity education. Its transparent design, explainability, and real-time performance make it a powerful tool for building digital trust. As phishing continues to evolve, solutions like SafeScan.Pro will play an essential role in both prevention and awareness.

# CONCLUSION

SafeScan.Pro is a comprehensive, intelligent, and educational response to the growing threat of phishing attacks in today’s increasingly connected digital world. As cybercriminals continue to exploit malicious URLs as common gateways for launching attacks, there is a clear and urgent need for effective, user-friendly security tools that can protect individuals and organizations. SafeScan.Pro rises to this challenge by providing a technically advanced yet accessible solution that integrates machine learning, feature engineering, external threat intelligence, and modern web technologies. At its core, the system uses a trained Random Forest model to accurately detect phishing URLs based on a carefully curated set of predictive features. These features are extracted through thoughtful analysis and preprocessing techniques that help the model differentiate between safe and malicious links.

The project further enhances its detection capabilities through integration with VirusTotal, a widely respected threat intelligence platform that aggregates data from multiple antivirus engines and URL scanners. This dual-layered approach combining custom machine learning with external validation adds robustness to the system’s predictions. The results are presented to users via a responsive and interactive web interface built using React, allowing for real-time scanning, intuitive navigation, and immediate, actionable feedback. This frontend not only enhances usability but also ensures that the technology remains accessible to both technical and non-technical users. Beyond its functionality as a security tool, SafeScan.Pro doubles as a powerful educational platform. It introduces students, developers, and cybersecurity enthusiasts to practical concepts such as data preprocessing, feature engineering, and the use of supervised machine learning models in real-world applications. It also covers the full-stack development pipeline, including RESTful API design, frontend development with React, integration of third-party APIs like VirusTotal, and real-time analysis workflows. Additionally, the project emphasizes best practices in software engineering, such as modular design, scalability, separation of concerns, and secure architecture, making it a valuable reference for aspiring developers.

As a Final Year Project (FYP), SafeScan.Pro reflects not only technical proficiency but also a deep understanding of real-world problems and the ability to craft effective solutions. It demonstrates how complex technologies can be translated into practical tools that have real impact. However, like all systems, it has certain limitations. The machine learning model, while effective, is trained on a static dataset and lacks the ability to adapt to emerging phishing patterns without retraining. The reliance on VirusTotal introduces potential issues such as API rate limiting and response delays, which can affect performance at scale. Additionally, the temporary exposure of API keys in the frontend during development poses a security risk that must be addressed before deploying the system to production. These limitations, however, are not weaknesses but valuable learning opportunities. They underscore the importance of secure coding practices, API key management, DevOps workflows, and continuous monitoring of deployed models. Addressing these issues provides insight into the lifecycle of a real-world software system from development and testing to deployment and maintenance. In this way, SafeScan.Pro not only solves a critical cybersecurity problem but also prepares its developers with the tools, knowledge, and mindset required for professional success in the tech industry.

In today’s hyper-connected world, the threat landscape continues to evolve, with phishing attacks emerging as one of the most persistent and damaging cybersecurity risks. These attacks often begin with a simple yet deceptive URL that appears legitimate but is designed to steal credentials, spread malware, or compromise systems. Conventional defenses like static blacklists or manual URL checking fail to keep pace with the rapid growth and obfuscation techniques employed by attackers. This reality called for an intelligent, real-time, and scalable solution leading to the development of SafeScan.Pro, a project designed to bridge this critical cybersecurity gap using machine learning and external threat intelligence.

The system is centered around a Random Forest classifier, selected due to its proven success in structured classification tasks, interpretability, low training time, and resilience to overfitting. The model was trained on a robust dataset of over 650,000 URLs, collected from trusted sources including PhishTank, Kaggle, and VirusTotal reports. Using a set of 11 carefully engineered features, the model learned patterns commonly associated with phishing URLs, such as irregular domain structures, excessive subdomains, presence of IP addresses, suspicious keywords, URL length, and unusual characters. This feature-driven approach not only improves detection accuracy but also makes the system explainable a vital requirement in cybersecurity tools.

The project’s unique strength lies in its hybrid architecture, which combines ML-based detection with the VirusTotal API, a globally recognized threat intelligence platform that scans URLs through more than 70 antivirus engines. This dual-layered verification system ensures that even if a URL bypasses one layer, it is likely to be caught by the other, significantly reducing false negatives. The integration of API-based validation also brings real-time global threat context into the prediction, making the tool more comprehensive than standalone models. Moreover, the model achieved impressive evaluation results over 91% accuracy, strong F1-Score, and a well-balanced confusion matrix, confirming its reliability for real-time prediction scenarios.

From a deployment perspective, SafeScan.Pro demonstrates how academic machine learning models can be translated into real-world applications. The system is implemented with a Flask backend that handles URL input, feature extraction, and model prediction, and a React + Tailwind frontend that allows users to input URLs and receive instant results. The architecture is modular, meaning future features or models can be added without major redesign. The solution is designed for everyday users from students to small businesses who may not have access to enterprise-grade cybersecurity tools but still need reliable protection against phishing threats.

The usability of SafeScan.Pro is a major achievement. By transforming a complex detection model into a clean, fast, and responsive user experience, the tool becomes accessible to non-technical users. It simplifies a serious cybersecurity task into a single action entering a URL. The backend’s real-time response and the frontend’s interactive design work together to reduce friction, promote awareness, and empower users to think before they click. Furthermore, the project aligns with modern trends in explainable AI (XAI), offering transparency into the detection process, which can be extended in the future to include visual explanations or user-friendly risk scores.

In conclusion, SafeScan.Pro stands as a successful proof-of-concept and fully functional system that merges academic rigor with real-world utility. It reflects a well-rounded project that involved end-to-end work from data preprocessing, feature engineering, model building, and evaluation, to full-stack deployment and live API integration. It addresses a real, growing threat with practical impact and scalability. With future enhancements such as multilingual phishing detection, browser extension deployment, or integration with messaging apps and email clients, SafeScan.Pro can evolve into a full-fledged cyber defense platform. The project not only meets its original goals but also establishes a strong foundation for further innovation in phishing detection and web security.

**Key Takeaways**

SafeScan.Pro identifies and explains phishing threats using ML and threat intelligence. It is modular, extensible, and suitable for both learning and lightweight production use. The project highlights the value of combining data science with practical web development. Its success lies in its clarity, transparency, and actionable insight offering users not just a verdict, but a full understanding of *why* a URL was flagged.

SafeScan.Pro successfully addresses the growing challenge of phishing attacks by combining machine learning with real-time threat intelligence. Using a Random Forest classifier trained on structured features like URL length, subdomains, and suspicious keywords, the system achieved high accuracy in detecting malicious URLs. The integration of the VirusTotal API further enhanced detection reliability by validating links against 70+ antivirus engines. Designed with a Flask backend and a React frontend, SafeScan.Pro is a fully functional, real-time web application that is both fast and user-friendly. Its modular architecture ensures scalability, while its simplicity makes it accessible to non-technical users. Overall, the project demonstrates how practical and intelligent cybersecurity solutions can be built using efficient models, thoughtful feature engineering, and clean user interface design.

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