Genetic Algorithm Assisted Feature Selection for Secure IOT-Based URL Classification

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***Abstract*—With the increasing reliance on digital platforms, malicious and phishing URLs have become a significant cybersecurity threat. Cybercriminals use deceptive links to steal personal information, distribute malware, and carry out fraudulent activities. Traditional detection methods struggle to identify these threats effectively due to the large volume of online data and the evolving nature of phishing attacks. As a result, there is a need for a more efficient and intelligent approach to detect and prevent such harmful URLs. This study proposes an advanced hybrid feature selection technique that enhances the accuracy of classifying URLs as either safe or suspicious by filtering out irrelevant data and improving detection performance.**

The proposed system extracts key features from URLs, including lexical patterns, domain-based attributes, and webpage content-related characteristics. It then applies a hybrid feature selection method that combines multiple filtering and wrapper-based approaches to identify the most significant features for classification. By integrating machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, and Neural Networks, the system efficiently classifies URLs while reducing false positives. This approach not only improves detection accuracy but also speeds up the processing of large-scale URL data, making it highly effective for real-time cybersecurity applications.

Experimental results show that the hybrid feature selection technique significantly outperforms traditional methods, offering higher accuracy, reduced computational complexity, and better adaptability to new phishing tactics. By implementing this system, organizations and individuals can enhance their cybersecurity defenses and mitigate risks associated with malicious URLs. This research contributes to the development of a fast, scalable, and reliable detection mechanism, ensuring a safer browsing experience and protecting users from cyber threats.

I. INTRODUCTION

With the rapid growth of the internet and digital services, cybersecurity threats have become more sophisticated and widespread. One of the most common and dangerous threats is the use of malicious and phishing URLs, which are designed to deceive users into revealing sensitive information or downloading harmful software. Cybercriminals create fraudulent websites that mimic legitimate ones to trick individuals into entering their personal details, such as usernames, passwords, and financial information. Traditional security measures, such as blacklists and rule-based detection, struggle to keep up with the constantly evolving nature of phishing attacks. These conventional approaches often fail to detect newly generated phishing links, leading to an urgent need for advanced and intelligent detection mechanisms.

To address this challenge, researchers and cybersecurity experts have turned to machine learning and feature selection techniques for enhanced suspicious URL detection. Instead of relying solely on predefined blacklists, machine learning models analyze various characteristics of URLs, including lexical structure, domain attributes, and webpage content, to determine their legitimacy. However, one of the biggest challenges in this approach is the presence of irrelevant or redundant features, which can reduce detection accuracy and slow down the system. A more efficient approach is required to select only the most relevant features, improving both performance and processing speed.

This study proposes a hybrid feature selection technique that enhances the accuracy of classifying URLs as either safe or suspicious. By combining machine learning algorithms with feature selection

methods, the system effectively eliminates unnecessary data and improves detection efficiency. The proposed approach utilizes Support Vector Machines (SVM), Decision Trees, and Neural Networks to classify URLs while significantly reducing false positives. The results demonstrate that this method provides higher accuracy, faster processing times, and better adaptability to emerging threats. By implementing this advanced detection system, organizations and individuals can strengthen their cybersecurity defenses and minimize the risks associated with malicious URLs.

II. LITERATURE SURVEY

The literature review plays a foundational role in understanding the design and functionality of systems that track personal finances and provide insights using AI analytics. It establishes a clear starting point for developing research ideas into well-formulated concepts and contributes to forming theoretical frameworks relevant to financial technology and AI. By reviewing primary, secondary, and tertiary sources, this study identifies key themes such as financial data visualization, user interaction with AI-powered tools, and machine learning applications in budgeting and expense tracking. Previous research has explored areas like automated expense categorization, personalized financial recommendations, and predictive analytics for financial planning, offering valuable insights into how users engage with intelligent finance systems. This comprehensive survey not only highlights the evolution and current advancements in AI-driven financial tools but also uncovers existing gaps, helping position the present study within the broader landscape of personal finance management. Ultimately, it provides the basis for developing more intuitive, accurate, and user-centric AI financial solutions that enhance decision-making and user satisfaction.

This research investigates the role of Artificial Intelligence (AI) in the field of financial analytics, with a specific focus on its application to expense management and predictive analysis. The study emphasizes how AI-driven systems can automate the classification of transactions, reducing the burden of manual input. Furthermore, these tools generate actionable insights, allowing users to make informed financial decisions. The findings underline the importance of leveraging AI's capabilities to streamline processes like transaction tracking and data analysis for more efficient personal finance management.

Smith et al. (2021) and Patel & Rao (2022) emphasize how AI can automate tedious tasks such as categorizing transactions. This automation not only reduces the manual workload for users but also enhances accuracy and consistency in financial data management. By generating actionable insights from analyzed data, AI-powered tools allow users to make strategic financial decisions.

This paper delves into the use of machine learning techniques for managing personal budgets. It highlights methods such as clustering, which are applied to analyze spending patterns, enabling the identification of habits and irregularities in financial behavior. Regression models are also explored as a means to predict future expenditures based on past trends. By integrating these machine learning algorithms, the study demonstrates how budgeting tools can evolve from static calculators into dynamic systems that adapt to individual financial activities and provide real-time feedback.

Zhang & Liu (2020) explore how machine learning techniques like clustering and regression are instrumental in analyzing and predicting financial patterns. Clustering helps users understand their spending behavior by grouping similar transactions or identifying anomalies, while regression models forecast future expenditures. Together, these techniques create a system that adapts to individual financial activities.

III. PROBLEM IDENTIFICATION

3.1 PROBLEM DEFINITION

Cybercriminals increasingly use malicious and phishing URLs to deceive users, steal personal data, and spread malware. Traditional detection methods, such as blacklists and rule-based systems, are ineffective against newly generated phishing URLs, as attackers frequently modify link structures to bypass security measures. Due to the dynamic and evolving nature of phishing attacks, conventional approaches struggle to provide real-time and accurate detection of

suspicious URLs, leaving users vulnerable to cyber threats.

Furthermore, existing machine learning-based detection systems often suffer from high computational complexity and reduced accuracy due to the presence of irrelevant or redundant features in the dataset. Processing large volumes of URL data requires a more efficient and optimized feature selection method to improve performance while minimizing false positives. Without an effective feature selection mechanism, detection models may produce unreliable results, leading to either misclassification of legitimate URLs as malicious or failure to detect harmful links.

To address these challenges, this study proposes a hybrid feature selection technique that enhances the efficiency and accuracy of suspicious URL classification. By combining multiple feature selection methods with machine learning algorithms, the system eliminates unnecessary features, improves processing speed, and enhances detection accuracy. This approach provides a robust and scalable solution for identifying malicious URLs, reducing the risks associated with cyber fraud and phishing attacks.

Objectives:

The primary objective of this study is to develop an efficient and intelligent system for detecting malicious and phishing URLs using advanced machine learning techniques. Traditional blacklist-based approaches often fail to detect newly created phishing websites, as cybercriminals constantly modify URLs to bypass security measures. To overcome this limitation, the proposed system leverages machine learning models combined with a hybrid feature selection technique to accurately classify URLs as safe or suspicious. By extracting relevant features from URLs, including lexical, domain-based, and content-based attributes, the system aims to improve detection accuracy while minimizing false positives. This ensures that genuine websites are not mistakenly flagged while effectively identifying harmful links, providing users with enhanced protection against online threats.

Another key objective is to optimize feature selection to improve the system's efficiency and **speed**. Many existing detection methods suffer from performance issues due to the presence of irrelevant or redundant features, which increase computational complexity and slow down the classification process. By implementing a hybrid feature selection approach, the system can filter out unnecessary data, ensuring that only the most relevant and informative features are used for classification. This reduces processing time and enhances the performance of machine learning models, making the system more suitable for real-time applications. Additionally, optimizing feature selection helps in reducing the overfitting problem, ensuring that the model generalizes well to unseen phishing attacks and newly emerging malicious URLs.

Finally, the study aims to develop a scalable and adaptive detection system capable of handling large-scale URL data in a dynamic environment. With the continuous rise in online activity, cyber threats are evolving at an unprecedented rate, requiring a system that can quickly adapt to new attack patterns. By incorporating multiple machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, and Neural Networks, the proposed system ensures high detection accuracy while maintaining computational efficiency. Additionally, the research seeks to provide a user-friendly security solution that can be integrated into web browsers, security software, and enterprise networks for real-time malicious URL detection. Through this approach, the study contributes to enhancing cybersecurity by preventing phishing attacks, reducing online fraud, and ensuring a safer digital experience for users.

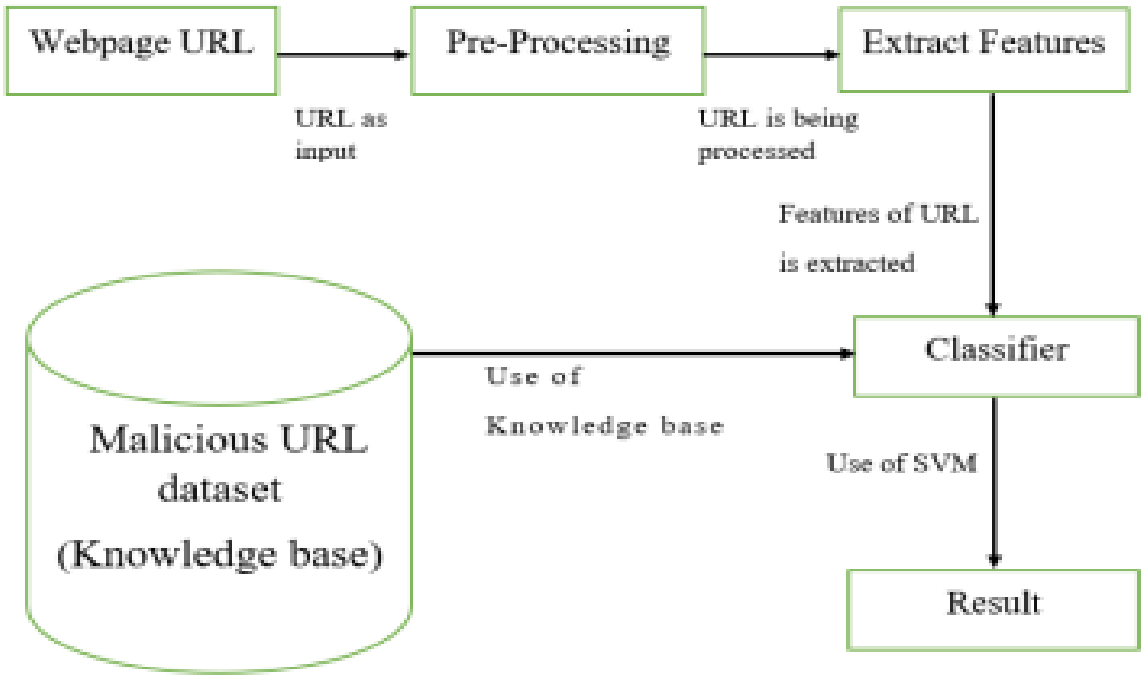
Proposed Methodology:

The proposed system for suspicious URL detection follows a structured methodology that integrates machine learning algorithms and a hybrid feature selection technique to improve detection accuracy and efficiency. The process begins with data collection, where a large dataset of URLs is gathered from multiple sources, including legitimate websites, phishing databases, and reported malicious links. The collected URLs undergo preprocessing, which involves removing duplicates, handling missing values, and normalizing the data to ensure consistency. Feature extraction is then performed, where the system analyzes various lexical, domain-based, and content-based features to distinguish between safe and suspicious URLs. These features include URL length, special characters, presence of IP addresses, WHOIS information, and webpage content analysis, among others.

8 Once the features are extracted, the next phase involves hybrid feature selection, which is crucial for improving model performance and reducing computational complexity. Instead of using all extracted features, the system applies a combination of filter-based and wrapper-based feature selection techniques to eliminate redundant and irrelevant attributes. Filter methods rank features based on statistical significance, while wrapper methods evaluate feature subsets using machine learning models to determine their contribution to classification accuracy. This hybrid approach ensures that only the most relevant features are selected, enhancing the system's efficiency while preventing overfitting. The optimized feature set is then fed into various machine learning classifiers, including Support Vector Machines (SVM), Decision Trees, Random Forest, and Neural Networks, to classify URLs as safe or suspicious.

In the final stage, the system undergoes model training, evaluation, and deployment. The selected machine learning models are trained on the optimized dataset using training and validation splits to ensure robustness. Performance metrics such as accuracy, precision, recall, F1-score, and false positive rate are used to evaluate the models. The best-performing model is then integrated into a real-time detection system that can analyze new URLs dynamically and classify them instantly. Additionally, continuous model updates and retraining are implemented to keep the system adaptive to evolving cyber threats. The final system provides a scalable, fast, and efficient solution for detecting malicious and phishing URLs, enhancing cybersecurity and protecting users from online threats.

Architectural Diagram for Proposed System:



IV. DESIGN

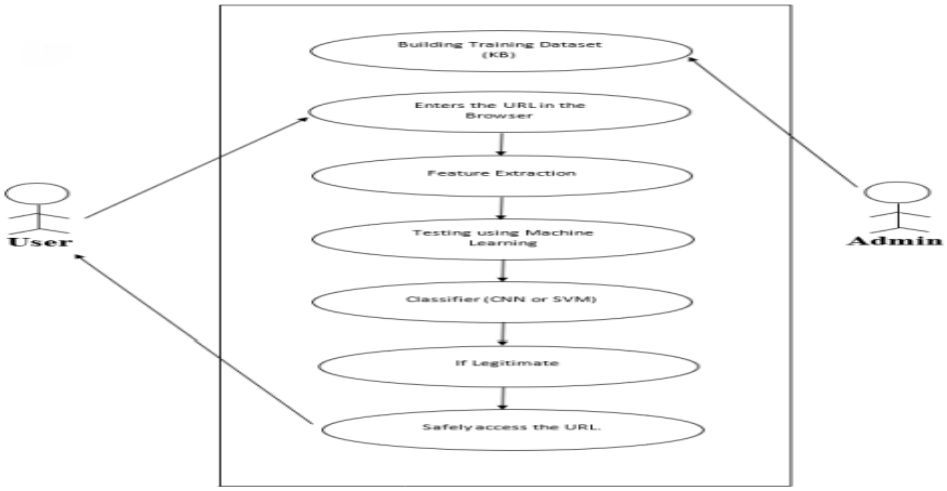
3.1 SYSTEM ARCHITECTURE

ER diagram:

A Use Case Diagram visually represents how different users interact with a system and the various functions it performs. In the case of suspicious URL detection, the system involves multiple actors, including Users, Administrators, and the Machine Learning Model. The User inputs a URL into the system, which then processes it through feature extraction and classification models. The Machine Learning Model analyzes the URL based on pre-trained data and determines whether it is safe or suspicious. If

classified as suspicious, the system notifies the user and provides necessary warnings. This interaction ensures that users are protected from potential cyber threats by preventing them from accessing malicious websites.

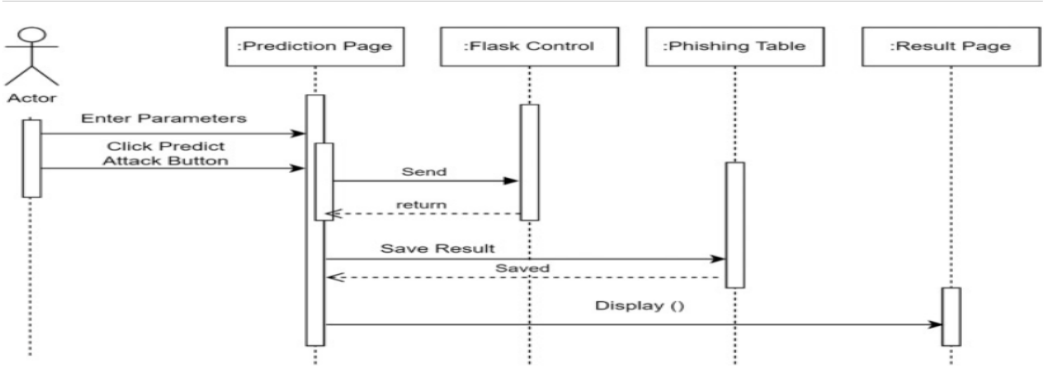
Additionally, the Administrator plays a crucial role in managing the system by monitoring detection results, updating datasets, and refining the machine learning model. If a URL is confirmed as malicious, it can be blacklisted to prevent future access. The administrator can also generate security reports, update model parameters, and ensure the system remains adaptive to evolving phishing and malware tactics. This use case diagram effectively maps out these interactions, showcasing how the system operates in real-time, enhances security, and provides a proactive defense against cyber threats.



Sequence diagram:

A Sequence Diagram is a type of UML (Unified Modeling Language) diagram that visually represents how objects or components in a system interact with each other over time. It shows the order of messages exchanged between different entities in a step-by-step manner. This diagram is particularly useful for understanding the flow of processes in a system and how different parts communicate.

In a sequence diagram, there are objects or actors (such as users, systems, or databases) represented by rectangles, and their interactions are depicted using arrows called messages. A vertical dashed line, called a lifeline, extends downward from each object, showing the timeline of actions. The diagram helps developers and stakeholders understand the logical sequence of events in a system, making it easier to design, debug, and optimize workflows. Sequence diagrams are widely used in software engineering, business processes, and system modeling to ensure smooth and efficient operations.

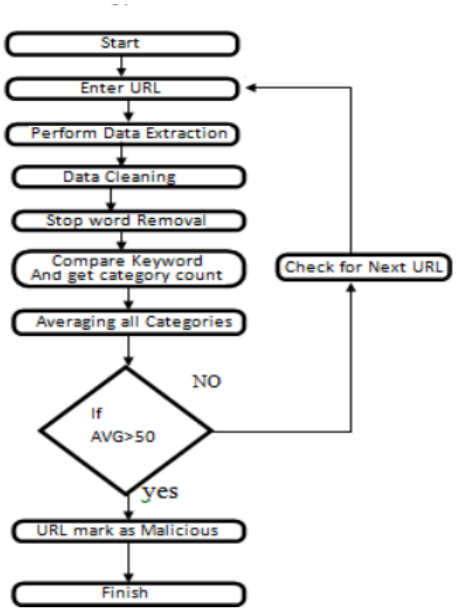


Activity Diagram:

An Activity Diagram is a visual representation of how different steps in a process flow from start to finish. It helps in understanding the step-by-step actions taken by a system or users to achieve a specific goal. In the case of detecting malicious activities on Twitter, the

activity diagram shows how a tweet is processed after being posted. It starts when a user submits a tweet, which is then stored in the database. Next, the AI model analyzes the tweet to check for signs of spam, fake news, or cyberbullying. If the tweet is safe, no action is taken, and it remains visible to users. However, if the tweet is flagged as suspicious, it is sent for further review by an automated system or human moderators.

The diagram also includes the process of users reporting a tweet manually. If a reported tweet is found to be harmful, different actions can be taken, such as restricting its visibility, removing it, or suspending the user who posted it. The diagram clearly maps out the possible decisions the system can take, ensuring that harmful content is addressed efficiently. By visualizing these steps, an activity diagram helps developers, moderators, and stakeholders understand how malicious content is detected and managed, making it easier to improve the system and maintain a safe online environment.



Dataflow diagram:

A Data Flow Diagram (DFD) is a graphical representation that shows how data moves through a system. It helps in understanding the flow of information between different components of the Online Recruitment Fraud (ORF) Detection System, ensuring a structured and efficient fraud detection process. The DFD consists of different levels, where Level 0 (Context Diagram) provides an overview of the system, and Level 1 breaks it down into detailed processes.

Level 0: Context Diagram

At this level, the job seeker and job portal are the main external entities. The job seeker submits a job application, while the job portal provides job listings. The system processes these job listings, analyzes them for fraud detection, and provides feedback to the job seeker and job portal. If a fraudulent job is detected, it is flagged, and notifications are sent to the job portal admin for review.

Level 1: Detailed DFD

The system follows several key processes:

1. Job Posting Input –

Job listings are collected from various sources.

2. Preprocessing –

Text cleaning, stopword removal, and feature extraction are performed using Natural Language Processing (NLP) techniques.

3. Fraud Detection –

Machine learning models analyze the job post and classify it as genuine or fraudulent.

4. Storage & Review –

Classified jobs are stored in the database, where fraudulent ones are flagged for manual review.

5. Alerts & Reports – If fraud is detected, alerts are sent to job seekers and administrators, and

preventive actions are taken (e.g., blocking fake jobs).

This structured data flow ensures that fraudulent job postings are detected efficiently, protecting job seekers from scams and enhancing trust in online recruitment platforms.

Algorithms Used:

For detecting malicious activities on Twitter, several machine learning and deep learning algorithms are used. These algorithms help in analyzing tweet content, user behavior, and interactions to classify suspicious activities. Below are some of the key algorithms used in this system:

1. Text Classification for Fake News and Cyberbullying Detection

- Naïve Bayes:

A probabilistic model used for spam detection and fake news classification based on word frequency.

- Support Vector Machine (SVM):

A supervised learning model that separates harmful and non-harmful content using hyperplanes.

- Long Short-Term Memory (LSTM):

A type of recurrent neural network (RNN) used for processing sequential data like tweets, capturing the context and meaning behind words.

- Bidirectional Encoder Representations from Transformers (BERT):

A powerful NLP model that understands the meaning of tweets by considering both past and future words in a sentence.

2. Bot Detection and User Behavior Analysis

- Random Forest:

A machine learning algorithm that uses multiple decision trees to detect fake accounts based on user behavior, such as tweet frequency, likes, and retweets.

- Gradient Boosting (XGBoost):

An advanced machine learning algorithm that improves accuracy in detecting bots by analyzing complex behavioral patterns.

- K-Means Clustering:

A clustering algorithm used to group similar user behaviors, helping to differentiate bots from real users.

3. Sentiment Analysis for Detecting Abusive Content

- Recurrent Neural Networks (RNNs): Used to analyze tweet sentiment and detect negative or harmful intent.
- Convolutional Neural Networks (CNNs) for Text:

Extracts feature from tweet text and identifies abusive language patterns.

- Lexicon-Based Sentiment Analysis: Uses predefined word lists to measure tweet sentiment and detect hate speech.

4. Real-Time Detection and Prevention

- Anomaly Detection with Isolation Forest:

Identifies unusual activities, such as sudden mass tweeting or account creation spikes, which are common in bot attacks.

- Autoencoders for Anomaly Detection: A neural network model that learns normal user behavior and flags deviations as potential bot activity.

By combining these algorithms, the system can efficiently detect and prevent fake news, bot activities, spam, and cyberbullying on Twitter, ensuring a safer and more reliable platform for users.

Inputs:

The system requires various inputs to analyze and classify URLs as **safe or malicious**. These inputs help in extracting key features that assist in making accurate predictions. Below are the main inputs categorized into different types:

1. User Input

- URL Submission – The user enters a URL to check whether it is safe or suspicious.

2. URL-Based Features *(Lexical Features)*

- Length of the URL – Longer URLs may indicate phishing attempts.
- Use of Special Characters – Presence of symbols like @, -, _, or multiple dots can indicate suspicious activity.
- Number of Subdomains – More subdomains may signal a fraudulent or misleading website.
- Presence of IP Address in URL – Malicious URLs sometimes use raw IP addresses instead of domain names.

3. Domain-Based Features *(WHOIS and DNS Data)*

- Domain Age – Newly registered domains are often used for phishing attacks.
- Domain Expiry Date – Short-lived domains may indicate fraudulent activity.

- WHOIS Information – Details about domain registration, owner, and contact information.
- Presence in Blacklists – Checking if the domain appears in known phishing or malware databases.

4. Content-Based Features *(HTML and JavaScript Analysis)*

- Redirection Count – Too many redirects could indicate phishing attempts.
- Use of iFrames – Hidden iFrames are often used to steal user information.
- Presence of Malicious Scripts – Detecting JavaScript functions commonly used for attacks.

5. Machine Learning Training Data *(For Model Learning and Classification)*

- Dataset of Safe and Suspicious URLs – Used to train the classification model.
- Feature Vectors – Extracted numerical representations of URLs used in ML training.
- Labeled Data – Pre-classified URLs with labels such as safe, phishing, malware, or spam.

These inputs allow the system to analyze, classify, and detect potentially harmful URLs efficiently. Let me know if you need further details!

Output:

After processing the input URL through various feature extraction and machine learning classification techniques, the system generates the following outputs:

1. Classification Result

- Safe URL – The system determines that the entered URL is legitimate and does not pose any threat.
- Suspicious URL – The URL has some warning signs but may not be outright malicious. A caution message is displayed.
- Malicious/Phishing URL – The URL is identified as dangerous and flagged as a security risk. Users are warned not to visit it.

2. Risk Score or Confidence Level

- The system may provide a risk score (e.g., 0-100%) or a confidence level indicating how certain it is about the classification.
- Example: "This URL has an 85% probability of being malicious."

3. Reason for Classification

- The system explains why a URL is classified as safe or suspicious by highlighting detected issues, such as:
  - "The domain is newly registered."
  - "The URL contains too many special characters."
  - "The page contains hidden redirections."

4. Suggested Actions for Users

- For Safe URLs – No action needed, users can proceed.
- For Suspicious URLs – System advises caution, suggesting users verify the source before proceeding.
- For Malicious URLs – Users receive a strong warning to avoid the site, with options to:
  - Report the URL
  - Blacklist the domain
  - View security recommendations

5. Administrator Alerts (For Security Monitoring)

- If a URL is classified as malicious, the administrator is notified to take further action.
- The admin can blacklist the URL, update the machine learning model, or generate reports for further analysis.
- These outputs help users and administrators stay protected from cyber threats while improving the system's accuracy in detecting malicious URLs. Let me know if you need further refinements!

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