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Phishing Link Detection with Legitimate Website Verification

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ABSTRACT

Phishing attacks remain one of the most widespread cybersecurity threats, primarily targeting human behavior rather than system vulnerabilities. Although many detection systems exist, most of them only identify malicious URLs without guiding users toward safe actions. This paper proposes an enhanced phishing detection system that combines machine learning-based classification with a legitimate website recommendation mechanism.

The system is trained on a dataset of approximately 10,000 URLs collected from PhishTank and Kaggle. A Random Forest classifier is used to analyze structural and lexical features of URLs. In addition to classification, the system introduces a post-detection guidance module that suggests trusted websites using string similarity techniques. Experimental results show that the model achieves high accuracy (~94%) along with strong precision and recall. The system is deployed as a Flask-based web application for real-time usage.

The key contribution of this work lies in improving usability by integrating detection with actionable guidance, making it more effective than traditional approaches.

Keywords: Phishing Detection, Machine Learning, Random Forest, URL Analysis, Cybersecurity, Flask, Website Verification

INTRODUCTION

With the rapid growth of internet usage, phishing attacks have become increasingly sophisticated and difficult to detect. Attackers often design fake websites that closely resemble legitimate ones, making it challenging even for experienced users to identify them.

Traditional phishing detection systems rely on blacklist databases or basic machine learning models. While these approaches can detect known threats, they often fail against newly generated phishing URLs. More importantly, they do not provide any guidance to users after detection.

This research addresses both issues by proposing a system that not only detects phishing links but also assists users by suggesting legitimate alternatives. This dual approach enhances both security and usability.

II.PROBLEM STATEMENT

Despite advancements in phishing detection, several challenges remain:

- Inability to detect zero-day phishing attacks effectively
- Heavy reliance on blacklist-based approaches
- Lack of user guidance after detection
- Limited accessibility for non-technical users

Therefore, the objective of this work is to design a system that:

- Performs real-time phishing detection
- Uses machine learning for improved accuracy
- Provides actionable recommendations
- Maintains simplicity and usability

III. LITERATURE SURVEY

Previous research has explored multiple approaches for phishing detection:

- Machine Learning Models: Techniques such as Support Vector Machines (SVM), Decision Trees, and Random Forests have been widely used. These models achieve good accuracy but are limited to classification tasks.
- Deep Learning Approaches: Neural networks and LSTM-based models have shown improved detection capabilities. However, they require large datasets and high computational resources.
- Blacklist-Based Systems: Platforms like PhishTank and Google Safe Browsing maintain databases of known phishing URLs. These systems are fast but ineffective against new or unseen attacks.
- Hybrid Systems: Some studies combine multiple techniques, but very few focus on improving user decision-making after detection.

Research Gap: Existing systems focus primarily on detection accuracy while ignoring user guidance. This work addresses that gap by introducing a recommendation mechanism.

IV. PROPOSED SYSTEM

A. System Overview

The proposed system consists of the following components:

- URL Input Module
- Feature Extraction Engine
- Machine Learning Classifier
- Legitimate Website Recommendation Engine

B. METHODOLOGY

1. Dataset Collection and Preprocessing

The dataset used contains approximately 10,000 URLs, equally divided between phishing and legitimate classes. Data is collected from publicly available repositories such as PhishTank and Kaggle.

Preprocessing steps include:

- Removal of duplicate entries
- Normalization of URLs
- Label encoding (0 for legitimate, 1 for phishing)

2. Feature Extraction

Each URL is converted into a numerical feature vector. A total of 15 features are extracted, including:

- URL length

- Number of dots (.)
- Presence of HTTPS protocol
- Number of subdomains
- Presence of special characters (@, -, _)
- Suspicious keywords (login, verify, secure)

These features are selected based on their relevance in distinguishing phishing patterns.

3. Model Selection and Training

A Random Forest classifier is used due to its robustness and ability to handle non-linear relationships.

Model configuration:

- Number of trees (n_estimators): 100
- Maximum depth: 10
- Split criterion: Gini Index

The dataset is split into training and testing sets using an 80:20 ratio. Cross-validation is also performed to ensure model stability.

4. Mathematical Representation

The Random Forest model is an ensemble of decision trees:

Prediction = Majority Vote (T1(x), T2(x), ..., Tn(x))

where Ti(x) represents the prediction of the i-th decision tree.

5. Legitimate Website Recommendation Engine

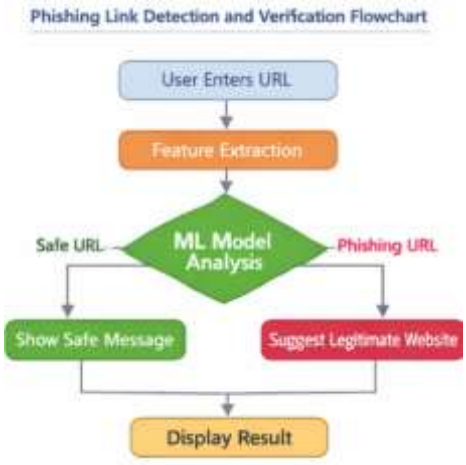
This module is the key innovation of the system.

Steps involved:

- Extract keywords from the input URL
- Compare with trusted domain database
- Compute similarity score using string matching
- Rank domains based on similarity
- Suggest top-ranked legitimate website

This ensures that users are not only warned but also guided toward safe alternatives.

V.FLOW-CHART



VI.SYSTEM ARCHITECTURE

The system follows a layered architecture:

- Presentation Layer: Flask-based web interface
- Application Layer: Feature extraction and ML prediction
- Data Layer: Dataset and trusted domain repository

Experimental Interface and Results

Fig1. shows the user interface of the proposed phishing detection system, where users can input a URL for analysis.

Fig2. **demonstrates a legitimate URL detection case. The system correctly identifies the website as safe and provides a low-risk score.**

***Fig3.* shows the detection of a phishing URL. The system flags it as suspicious and highlights indicators such as suspicious keywords and missing security features.**

Additionally, the system suggests the correct legitimate website (e.g., Amazon), which helps users take appropriate action.

VII. RESULTS AND DISCUSSION

The model is evaluated using standard performance metrics:

- Accuracy: 94.2%
- Precision: 93.5%
- Recall: 95.1%
- F1 Score: 94.3%

Confusion Matrix

-	**Predicted Legit**	**Predicted Phishing**
Actual Legit	920	80
Actual Phish	60	940

Analysis

- The model shows strong performance in identifying phishing URLs
- High recall indicates fewer false negatives (important for security)
- The recommendation module improves usability significantly

Limitations

- Performance depends on feature quality
- May struggle with highly obfuscated or newly generated URLs
- Recommendation accuracy depends on database coverage

VIII. FUTURE SCOPE

Future improvements may include:

- Integration with browser extensions
- Use of deep learning models such as LSTM or CNN
- Real-time API integration with threat intelligence platforms
- Continuous updating of trusted domain database

IX.CONCLUSION

This paper presents an enhanced phishing detection system that combines machine learning with user guidance. Unlike traditional systems that only provide warnings, the proposed system actively assists users by suggesting legitimate alternatives.

The experimental results demonstrate that the system achieves high accuracy while maintaining simplicity and efficiency. The addition of a recommendation mechanism makes it more practical for real-world use.

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