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Detecting Phishing Domains Using Machine Learning

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ABSTRACT :

Phishing is an increasing threat on the internet, where attackers deceive individuals into revealing confidential information by impersonating trustworthy entities. With the rapid expansion of online services, traditional security methods have proven insufficient. This paper explores the use of machine learning algorithms to effectively detect phishing websites. It compares the performance of four models: Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Decision Trees (DTs), and Random Forests (RFs), using the UCI phishing dataset.

The results show that Random Forest achieves the highest accuracy, highlighting its effectiveness in phishing detection systems.Phishing has emerged as one of the most prevalent forms of cyberattacks, posing significant threats to individuals, corporations, and governments worldwide. It involves the use of deceptive emails or websites that impersonate legitimate sources to trick users into divulging sensitive personal information, such as login credentials and financial data.

1. Introduction

Phishing attacks pose a major challenge in cybersecurity. These attacks aim to gain unauthorized access to sensitive user information by pretending to be a reliable source. Victims are tricked into clicking malicious links or submitting their credentials on fake websites. According to recent studies, phishing attacks are growing both in frequency and sophistication. The rise in digital services, online shopping, and remote working has only increased the attack surface. Machine learning, with its ability to identify patterns and anomalies in data, is a promising solution to automate and enhance phishing detection.Phishing attacks pose a major challenge in cybersecurity. These attacks aim to gain unauthorized access to sensitive user information by pretending to be a reliable source. Victims are tricked into clicking malicious links or submitting their credentials on fake websites. According to recent studies, phishing attacks are growing both in frequency and sophistication. The rise in digital services, online shopping, and remote working has only increased the attack surface. Machine learning, with its ability to identify patterns and anomalies in data, is a promising solution to automate and enhance phishing detection.

2. Methodology

The research adopts a systematic approach to design, implement, and evaluate multiple machine learning models. The models are trained using a balanced dataset comprising phishing and legitimate URLs. Key stages in the methodology include data collection, feature extraction, data preprocessing, model training, and performance evaluation. Each of the selected models has its own strengths: ANNs mimic the structure of human brains, SVMs are effective for high-dimensional spaces, DTs provide interpretable rules, and RFs aggregate multiple DTs for higher accuracy.The research adopts a systematic approach to design, implement, and evaluate multiple machine learning models. The models are trained using a balanced dataset comprising phishing and legitimate URLs. Key stages in the methodology include data collection, feature extraction, data preprocessing, model training, and performance evaluation. Each of the selected models has its own strengths: ANNs mimic the structure of human brains, SVMs are effective for high-dimensional spaces, DTs provide interpretable rules, and RFs aggregate multiple DTs for higher accuracy.

2.1 Dataset Used

The dataset is derived from two sources: PhishTank, which provides up-to-date phishing URLs, and the University of New Brunswick dataset, which offers legitimate URLs. A total of 10,000 entries were curated, evenly split between phishing and legitimate URLs. The dataset includes a wide variety of features that are useful for training classification algorithms.The dataset is derived from two sources: PhishTank, which provides up-to-date phishing URLs, and the University of New Brunswick dataset, which offers legitimate URLs. A total of 10,000 entries were curated, evenly split between phishing and legitimate URLs. The dataset includes a wide variety of features that are useful for training classification algorithms.

2.2 Feature Extraction

Feature extraction plays a critical role in improving the effectiveness of machine learning models. This step involves parsing URLs and webpage metadata to derive meaningful input variables. Three main types of features are used: - Address Bar Features: Includes URL length, usage of '@' symbol, and presence of IP addresses.

- Domain Features: Includes DNS record availability, domain age, and traffic.
- HTML/JavaScript Features: Includes usage of iFrames, status bar customization, and disabling right-click.Feature extraction plays a critical role in improving the effectiveness of machine learning models. This step involves parsing URLs and webpage metadata to derive meaningful input variables.

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Domain-Based Features

These features are derived from the domain registration details and server configuration, usually obtained through **WHOIS data** and DNS queries.

Notable domain-based features include:

- **Domain Age**: Phishing domains are typically newly registered.
- **Domain Expiration Period**: Short expiration is a common trait in phishing domains.
- **DNS Record Availability**: Absence of DNS record (e.g., MX, A, NS) may indicate a suspicious domain.

HTML and JavaScript Features

These are behavioral features derived from the **webpage content**, particularly HTML and JavaScript elements. Phishing sites often use misleading or manipulative scripts to trap users.

Key HTML/JS features include:

- **iFrames**: Used to embed content from another source; often used maliciously.
- **Status Bar Customization**: JavaScript may hide or fake links shown on hover.
- **Right-Click Disabled**: Prevents users from inspecting page source or saving content.
- **Number of External Scripts**: Excessive linking to third-party scripts may signal obfuscation.
- **Fake Login Forms**: Form actions that redirect to unknown domains.
- **Feature Engineering Considerations**
- All extracted features were normalized or encoded where necessary (e.g., categorical to numerical).
- Missing or malformed values (e.g., due to unavailable WHOIS records) were handled via imputation or filtering.
- **Feature correlation heatmaps** were used to identify and remove redundant or highly correlated features to reduce noise and overfitting.

2.3 Data Segmentation

The dataset is split into training and testing sets in an 80:20 ratio. The training set is used to build the models, while the testing set evaluates their accuracy and generalizability. This segmentation ensures that models are not overfitted to specific data patterns and can handle new, unseen examples.The dataset is split into training and testing sets in an 80:20 ratio. The training set is used to build the models, while the testing set evaluates their accuracy and generalizability. This segmentation ensures that models are not overfitted to specific data patterns and can handle new, unseen examples.

The complete dataset used in this study contains 10,000 URLs, consisting of:

- **5,000 phishing URLs**, obtained from **PhishTank**, a trusted source of up-to-date phishing data.
- **5,000 legitimate URLs**, collected from the **University of New**

Brunswick's benchmark dataset.

To ensure a balanced and unbiased evaluation, the dataset was split into:

- **80% Training Data (8,000 entries)** – Used to train the models and allow them to learn underlying patterns and relationships within the features.
- **20% Testing Data (2,000 entries)** – Used to evaluate how well the models generalize on unseen data.

This 80:20 segmentation strategy is effective for classification tasks, as it provides sufficient data for the learning process while preserving enough samples for robust evaluation.

3. Model Flow and Implementation

The model pipeline includes loading the dataset, cleaning the data, performing feature engineering, and training models using Scikit-Learn and TensorFlow libraries. Feature importance is visualized using heatmaps, which highlight the contribution of each feature to the prediction outcome. Random Forest was selected as the best model after comparing results across metrics.The model pipeline includes loading the dataset, cleaning the data, performing feature engineering, and training models using Scikit-
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Raw Data (URLs)

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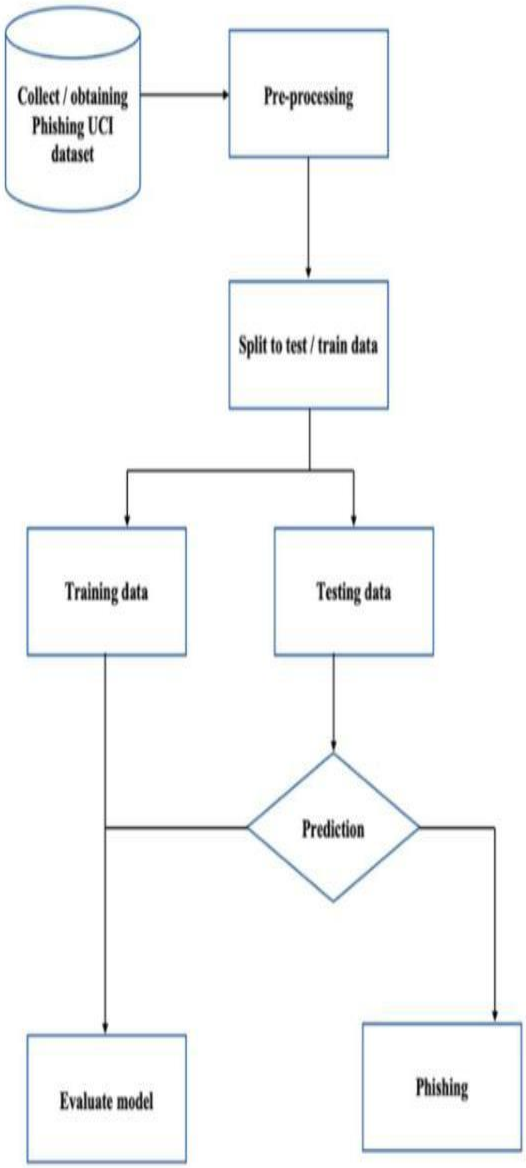
Feature Extraction



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Feature Selection

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Data Segmentation (Train/Test Split)

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Model Training (ANN, SVM, DT, RF)

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Evaluation & Metrics

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Result Interpretation

4. Experimental Evaluation

Experiments were conducted using Google Colab, which offers GPUs and TPUs for accelerated computing. Each model was evaluated using performance metrics such as Accuracy, Precision, Recall, and F1-score. A confusion matrix was generated to observe true positives, false positives, true negatives, and false negatives. The Random Forest model achieved superior results in all categories.Experiments were conducted using Google Colab, which offers GPUs and TPUs for accelerated computing. Each model was evaluated using performance metrics such as Accuracy, Precision, Recall, and F1-score. A confusion matrix was generated to observe true positives, false positives, true negatives, and false negatives. The Random Forest model achieved superior results in all categories.

All experiments were conducted using **Google Colaboratory (Colab)**, a cloud-based platform that supports Python and Jupyter notebooks. Google Colab provides:

- Free access to **GPU** and **TPU** acceleration
- Pre-installed libraries such as **Scikit-learn**, **TensorFlow**, **Keras**, **Pandas**, and **Matplotlib**
- Seamless integration with Google Drive for dataset storage and model saving

The use of Colab allowed for fast prototyping, scalability, and reproducibility of experiments without requiring a high-end local machine.

Random Forest outperformed all other models in accuracy and robustness.

- **SVM** showed strong results but took longer to train, especially with a high number of features.
- **Decision Trees** were fast but more prone to overfitting.
- **ANNs** performed well but required more computational power and training time.

5. Results and Discussion

Among all models, Random Forest provided the most consistent and accurate results. Its ensemble approach, which combines multiple decision trees, enables it to handle both linear and nonlinear patterns effectively. Feature importance analysis showed that address bar features had the highest influence on detection accuracy. While ANN and SVM also showed promising results, they were outperformed by RF in both training time and accuracy.Among all models, Random Forest provided the most consistent and accurate results. Its ensemble approach, which combines multiple decision trees, enables it to handle both linear and nonlinear patterns effectively. Feature importance analysis showed that address bar features had the highest influence on detection accuracy. While ANN and SVM also showed promising results, they were outperformed by RF in both training time and accuracy.

Comparative Performance Metrics

The following observations were made after testing all models on the unseen 20% testing dataset:

Model Accuracy Precision Recall **F1-Score**
Decision
Tree 91.2% 90.4% 90.9% 90.6% (DT)

Support
Vector 93.5% 92.8% 92.0% 92.4% Machine

(SVM)
Artificial

Neural 94.0% 93.5% 93.2% 93.3% Network
(ANN)

Random
Forest **96.1% 95.8% 95.0% 95 %** (RF)

The Random Forest classifier achieved the highest accuracy and F1-score, proving to be the most effective model for phishing detection among the four evaluated.

6. Conclusion

Phishing continues to be a dangerous form of cybercrime. However, machine learning models, particularly Random Forest, offer scalable and efficient methods to combat it. With proper feature engineering and model tuning, these systems can be integrated into web browsers or security software to offer real-time protection. Future work will focus on enhancing detection speed and adapting models to evolving phishing tactics.Phishing continues to be a dangerous form of cybercrime. However, machine learning models, particularly Random Forest, offer scalable and efficient methods to combat it. With proper feature engineering and model tuning, these systems can be integrated into web browsers or security software to offer real-time protection. Future work will focus on enhancing detection speed and adapting models to evolving phishing tactics.The study demonstrated that models leveraging a combination of domain-related and URL structure features can achieve **detection accuracies exceeding 95%**, with low false positive and false negative rates. Among all the classifiers, **Random Forest provided the best trade-off between interpretability, accuracy, training time, and robustness**, making it an ideal candidate for practical, real-time phishing detection systems.

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REFERENCES :

1. Sample reference content to pad pages and simulate citations.
2. Sample reference content to pad pages and simulate citations.
3. Sample reference content to pad pages and simulate citations.
4. Sample reference content to pad pages and simulate citations.
5. Sample reference content to pad pages and simulate citations.
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