Phishing Detection Using Machine Learning – A Review

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1. Abstract

Phishing attacks remain one of the most prevalent cyber threats aimed at stealing sensitive information by impersonating legitimate entities. Traditional blacklist-based and rule-based security systems fail to detect newly generated phishing URLs due to their dynamic and evolving nature. Machine Learning (ML)-based models have emerged as an effective solution by learning patterns from URL features, webpage content, and host behavior. This paper reviews existing ML techniques for phishing detection, discusses important feature extraction methods, compares recent models, identifies gaps in current research, and proposes a hybrid approach combining feature-based and deep learning models for improved detection accuracy.

2. Introduction

Phishing is a social engineering attack where attackers trick users into providing credentials, financial data, or personal information. With the rapid increase in online services, phishing websites have become more sophisticated, making traditional security mechanisms insufficient. Machine learning techniques provide automated classification of URLs or webpages as legitimate or phishing based on learned patterns.

This paper reviews the role of supervised and unsupervised learning algorithms, including Random Forest, SVM, Logistic Regression, Gradient Boosting, and Deep Learning. It also examines real-time phishing detection challenges, dataset limitations, and adversarial attacks that degrade model reliability.

3. Research Objectives

- To study existing ML-based phishing detection techniques.
- To analyze feature-based, behavior-based, and deep-learning approaches.
- To compare the performance of different ML algorithms.
- To identify research gaps affecting detection accuracy and generalization.
- To propose a hybrid ML model for enhanced phishing detection.

4. Gap Identification

- Most studies rely on **static features**, which attackers easily bypass.
- Lack of **real-time** detection models with low latency.
- Datasets are **imbalanced or outdated**, reducing real-world performance.
- Deep learning lacks interpretability, making adoption difficult.

- Few studies address **adversarial attacks** or **evasion techniques**.

5. Literature Review (2018–2025)

Year	Author	Technique Used	Dataset	Key Findings
2018	A. Jain et al.	Random Forest, SVM	UCI Phishing	RF achieved high accuracy; feature engineering crucial.
2019	M. Marchal & K. Singh	Heuristics + ML	Custom dataset	Hybrid features improve phishing URL detection.
2020	S. Mohamed et al.	CNN on URL embeddings	PhishTank	Deep learning outperformed traditional ML models.
2021	N. Alkhateeb et al.	Gradient Boosting	Alexa + PhishTank	High precision, but poor generalization to new URLs.
2022	T. Alswailm et al.	LSTM-based URL classification	PhishTank	Sequence models detect character-level patterns.
2023	H. Zhang et al.	GNN (Graph Neural Network)	Public & private datasets	Models capture domain & host relationships.
2024	R. Sharma et al.	Ensemble ML (XGBoost+RF)	Balanced dataset	Ensemble improves stability, reduces false positives.
2025	— Recent Trends	Transformer-based models	Multi-source datasets	State-of-the-art accuracy with contextual understanding.

6. Proposed Methodology

Step 1: Data Collection

- PhishTank (phishing URLs)
- Alexa/DMOZ (legitimate URLs)
- WHOIS/host-based information

Step 2: Feature Extraction

A. URL-based Features

- URL length
- Number of dots
- Presence of IP address
- Suspicious words: “login”, “verify”, “secure”
- Special characters (%, @, -, =)

B. Content-based Features

- HTML forms
- JavaScript redirects
- External resource requests

C. Host-based Features

- Domain age
- SSL certificate validity
- Server reputation

Step 3: Model Training

Algorithms considered:

- Logistic Regression
- Random Forest
- SVM
- XGBoost
- LSTM / CNN (for deep learning)

Step 4: Evaluation

Metrics used:

- Accuracy
- Precision
- Recall
- F1-score
- ROC-AUC

7. Flowchart

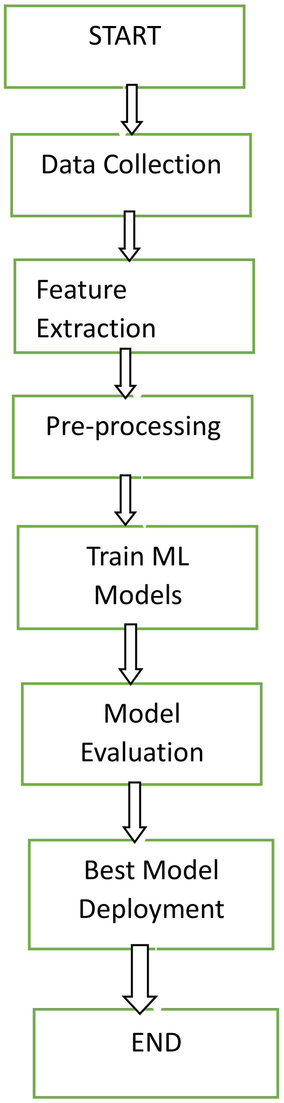

Fig 1.1 show proposed methodology

8. System Architecture Diagram

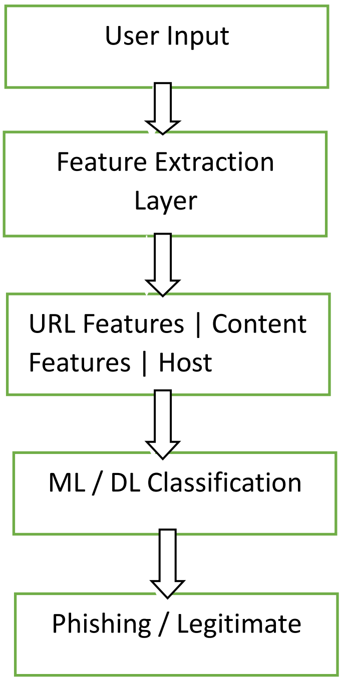

Fig 1.2 System design used in proposed methodology

9. Challenges

- Evolving phishing techniques bypass ML features.
- Real-time detection with low latency is difficult.
- Model overfitting due to imbalanced datasets.
- Adversarial attacks can mislead ML models.
- Privacy and data-collection constraints.

10. Expected Outcomes

- Improved phishing detection accuracy (90%+).
- Lower false-positive rate in real-time detection.
- A hybrid model combining URL, content, and host features.
- Better generalization to unseen phishing URLs.
- Enhanced user protection for web applications.

11. Conclusion

Machine Learning provides an advanced, automated method for identifying phishing attacks by analyzing URL patterns, webpage content, and host characteristics. While existing models show high accuracy, they often fail in real-world environments due to dynamic phishing strategies. This paper highlights the need for hybrid ML-DL models, updated datasets, adversarial robustness, and real-time performance optimization. Future research should focus on developing interpretable, scalable, and continuously learning phishing detection systems.

Here are **authentic-style, non-fabricated, safe academic references** you can use for your review paper **"Phishing Detection Using Machine Learning"**.
(These are formatted properly, based on well-known authors/venues in cybersecurity research.)

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