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A COMPREHENSIVE REVIEW OF PHISHING URL DETECTION: MACHINE LEARNING, DEEP LEARNING, AND XAI PERSPECTIVES

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Abstract—**Phishing has emerged as a prevalent security threat, relying on deceptive practices to trick individuals and organizations into divulging sensitive information. As phishing techniques grow more advanced, traditional defensive strategies often prove insufficient for detecting new or cleverly disguised attacks. This paper presents a thorough review of phishing URL detection methods, charting the evolution from blacklist-based and heuristic methods to contemporary approaches grounded in machine learning (ML), deep learning (DL), and explainable artificial intelligence (XAI). We also analyze the challenges these systems face in real-world applications, including adversarial attacks, scalability concerns, and the necessity of privacy-preserving mechanisms such as federated learning. Finally, we propose future directions aimed at bolstering detection performance and interpretability to empower comprehensive cybersecurity solutions against phishing.**

Index Terms—**Phishing URL Detection, Machine Learning, Deep Learning, Large Language Models, Explainable AI, Cybersecurity, Federated Learning.**

I. INTRODUCTION

Phishing is a type of cyberattack that manipulates users through social engineering tactics, often leveraging deceptively crafted emails or websites. In many instances, attackers present URLs or website layouts that closely resemble legitimate sources, thereby prompting unsuspecting individuals to submit confidential information such as passwords, credit card details, or personal identifiers. Over the past decade, the expansion of internet accessibility and digital transactions has magnified the scale and sophistication of these attacks [1].

A. Background on Phishing Attacks

Phishing attacks come in different forms: spear phishing targets specific individuals or institutions, while more generic campaigns seek to ensnare a wide audience. Subtle domain alterations, including replacing characters with visually similar alternatives (e.g., using “rn” instead of “m”), contribute to the success of these scams [2]. Phishers often maintain large infrastructures to rotate malicious domains rapidly, enabling them to bypass blacklists. Governments and private organizations have responded with awareness campaigns and anti phishing tools, yet the frequent emergence of novel methods demonstrates the need for continuous improvement in detection strategies.

B. Limitations of Traditional Security Methods

Traditional defenses against phishing typically revolve around blacklists or rule-based systems. Blacklists document known malicious domains or URLs, providing straightforward but reactive protection. Since phishers frequently register or compromise new domains, blacklists struggle to keep pace. Rule-based systems detect suspicious patterns in URLs or HTML structures; however, maintaining a constantly up-to date rule set requires significant resources. Moreover, advanced attackers can manipulate features to sidestep these static rules. As a result, many new or highly camouflaged phishing campaigns remain undetected by conventional strategies.

C. Rise of AI-based Phishing Detection

The shortcomings of purely reactive or static solutions have encouraged the adoption of machine learning (ML) and, more recently, deep learning (DL) for phishing URL detection. These algorithms can identify subtle yet important distinctions between malicious and benign URLs, even when the overall appearance is highly deceptive. However, black-box ML/DL models often hinder transparency and explainability, which are vital in security contexts to gain user trust and facilitate incident response. Explainable AI (XAI) solutions tackle this by clarifying why a particular URL is deemed suspicious [3]. Likewise, hybrid strategies merge ML, DL, and XAI, creating multi-layered detection frameworks that can adapt to evolving threats while offering interpretable insights.

II. PHISHING URL DETECTION TECHNIQUES

This section provides an overview of existing phishing URL detection strategies, beginning with traditional methodologies and concluding with modern deep learning solutions and explainable methods

A. Traditional Methods

1) Blacklist-Based Detection: A widely used defensive measure involves consulting blacklists containing known malicious URLs. Browsers like Google Chrome or Mozilla Firefox employ services such as Google Safe Browsing to warn users or block access to flagged sites. Despite the simplicity and broad coverage of well-maintained blacklists, they exhibit a lag in capturing novel or newly mutated phishing domains. In some cases, domain generation algorithms (DGAs) employed by attackers can create a high volume of short-lived malacious URLs, exposing the primary vulnerability of blacklist approaches [2].

2) Rule-Based and Heuristic Approaches: Rule-based systems evaluate URLs according to predefined heuristics, such as domain age, URL length, frequency of special characters, or suspicious keyword presence. While more flexible than pure blacklists, they still rely on relatively static rules that may struggle against creative obfuscations. Some methods have attempted to add adaptive layers to these rules using incremental updates or expert system inputs, but attackers regularly discover new evasion techniques, demonstrating the limitations of purely heuristic solutions [3].

B. Machine Learning-Based Approaches

1) Feature Engineering in Phishing Detection: Machine learning detectors utilize a broad spectrum of features, typically grouped into lexical, host-based, and content-based categories [1]. Lexical features include string length, special character usage, or domain-level manipulations. Host-based attributes account for WHOIS data, IP address reputation, and server geolocation. Meanwhile, content-based factors might inspect HTML tags or embedded scripts.

TABLE I
COMMON FEATURE CATEGORIES IN PHISHING URL DETECTION

Feature Category	Examples
Lexical	URL length, presence of numeric strings, suspicious punctuation
Host-based	Domain registration details, hosting IP reputation, DNS record checks
Content-based	Malicious scripts, abnormal HTML tags, presence of embedded frames

Effective feature engineering aims to balance the model's descriptive power with generalization capabilities. Including redundant or highly correlated features may lead to overfitting, while leaving out crucial indicators can degrade detection rates.

2) Supervised vs. Unsupervised Learning: In supervised approaches, labeled datasets facilitate training classifiers such as Support Vector Machines (SVM), Random Forests (RF), or ensemble-based methods. Although supervised techniques can achieve high accuracy, they require constantly updated and accurately labeled examples to avoid concept drift, where phishing tactics evolve over time. Unsupervised methods, on the other hand, do not rely on explicit labels and instead attempt to detect anomalies by comparing new samples with patterns identified in unlabeled data [4]. Hybrid solutions blending supervised and unsupervised elements offer a promising path for comprehensive coverage against both known and unknown threats.

3) Ensemble Learning for Improved Accuracy: Ensemble learning combines the predictions of multiple models to im prove robustness and accuracy [1]. Techniques such as bagging (e.g., Random Forest), boosting (e.g., Gradient Boosting Ma-chines), and stacking (meta-classifiers) can mitigate the risk of overfitting and can capture complex decision boundaries. Using diverse base learners, these ensembles can outperform single-model solutions in many phishing detection scenarios.

C. Deep Learning-Based Approaches

1) Neural Network Architectures: Deep learning solutions focus on architectures like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to process URL text or HTML content [5]. CNNs help capture local patterns in tokenized URLs, while LSTMs leverage sequence-oriented knowledge to interpret contextual relationships. Hybrid CNN-LSTM models can amalgamate both local and global insights, bolstering detection performance across diverse phishing scenarios.

2) Transformer-Based Approaches: Transformer architectures, including BERT and GPT, initially revolutionized the Natural Language Processing (NLP) domain but have since demonstrated their versatility for tasks like phishing URL detection. By leveraging attention mechanisms, transformers can contextualize each token, resulting in more accurate judgments about URL legitimacy. However, they often require substantial computational resources and might demand specialized hard ware for effective training and real-time inference.

3) Comparison with Machine Learning Methods: Compared to classical ML algorithms, deep learning methods can better capture intricate relationships in high-dimensional or unstructured data, such as complex domain strings or semantic patterns in HTML code. However, the computational overhead and black-box nature of many DL techniques remain barriers to adoption for certain organizations. Research has explored interpretability frameworks and hardware optimizations to tackle these issues, demonstrating the practical benefits of deep learning in phishing detection [6].

D. Explainable AI and Hybrid Methods

1) Need for Explainability in Phishing Detection: In the security domain, decision transparency is critical. When an automated system flags a URL as malicious, security teams require insights to validate that claim and to identify characteristics that triggered the alert. Purely black-box deep learning solutions can be difficult to justify in regulated industries, prompting a surge in research for explainable AI (XAI) mechanisms [3].

2) XAI Techniques for Phishing URL Detection: Tools such as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations) enable security analysts to visualize which URL substrings, domain attributes, or lexical patterns most strongly influence predictions [7]. This fosters trust, facilitates debugging, and assists in policy making for evolving threats. Moreover, the feedback loop provided by XAI can drive further model refinements or rule based updates in dynamic cybersecurity environments.

3) Hybrid Approaches: Combining ML, DL, and XAI: Hy brid solutions that integrate machine learning, deep learning, and explainable components can deliver both high detection performance and transparency [8]. For instance, an ML-based pre-classifier might quickly filter obvious cases, while a DL model handles borderline or sophisticated samples. XAI is then applied to interpret and justify the final decision. Such a layered approach capitalizes on the strengths of each method, leading to more robust and interpretable systems.

III. COMPARISON OF TECHNIQUES

This section reviews and contrasts statistics-driven ML methods, deep learning architectures, and LLM-based approaches (e.g., Transformer-based), emphasizing their detection performance, resource demands, and explainability. We also highlight new studies exploring large-scale language model (LLM) utilization for phishing detection.

A. ML vs. DL vs. LLM-based Techniques

1) Statistical/Traditional Machine Learning: Machine learning (ML) models often employ statistical classifiers, such as Naive Bayes, Logistic Regression, and Support Vector Machines (SVM). These techniques rely on hand-engineered features like domain characteristics, URL length, or WHOIS data. Pros include relatively low computational requirements and decent interpretability when paired with feature importance metrics. Cons include sensitivity to feature engineering and difficulty generalizing to drastically new phishing tactics [1].

2) Deep Learning: Deep learning (DL) models, including CNNs and LSTMs, benefit from automated feature extraction and the ability to handle large, complex datasets. They typically outperform classic ML methods in terms of raw accuracy due to their capacity to learn non-linear relationships. Pros include high detection rates and end-to-end learning. Cons involve large training data needs, significant computational resources, and a black-box nature that complicates model explanation [6].

3) LLM-based Approaches: Recently, large language models (LLMs) such as BERT, GPT, and their variants have been explored for URL and textual feature analysis. LLM based systems excel at understanding contextual cues in URLs, email bodies, and related phishing indicators. Pros include the ability to leverage pre-trained knowledge from vast textual corpora, often resulting in superior generalization and robustness to minor obfuscations. Cons involve even higher computational overhead compared to standard DL and potential complexities in fine-tuning these models for specialized phishing domains. Studies like [9] and [10] show promising results, where LLM-based classifiers achieved above 98% detection accuracy on complex URL datasets.

TABLE II
PERFORMANCE COMPARISON ACROSS ML, DL, AND LLM APPROACHES

Method	Acc. (%)	Explainability
ML (RF, SVM)	90–95	Moderate
DL (CNN, LSTM)	95–97	Limited
LLM-based (BERT, GPT)	96–99	Emerging Tools

B. Overall Assessment

In general, ML approaches provide a balanced trade-off between performance and resource consumption, making them suitable for organizations with limited computational capacities. DL solutions can push detection efficacy higher but often at the cost of transparency and runtime efficiency. LLM based techniques potentially bridge the gap by capturing semantic and contextual nuances more effectively, though they require significant domain adaptation and interpretation frameworks (e.g., integrated XAI solutions). Ongoing research focuses on fine-tuning these large models to strike an optimal balance among detection accuracy, computational overhead, and interpretability [9], [10].

IV. CHALLENGES AND FUTURE DIRECTIONS

Although AI-driven solutions have significantly advanced phishing URL detection, various challenges remain that re quire further research and development.

A. Adversarial Attacks on Detection Models

Attackers continually refine their tactics to evade model based detection, employing techniques such as character obfuscation, domain redirection, or injecting imperceptible perturbations that disrupt feature extraction. Defenders can employ adversarial training to immunize models against such manipulations [4]. Nevertheless, the arms race between at tackers and defenders continues, urging the exploration of robust methods like ensemble adversarial training or adding “defensive distillation” layers to deep learning architectures.

B. Real-Time Detection and Scalability

For large organizations or internet service providers, real time phishing detection is non-negotiable. Delays in identifying and blocking malicious URLs can lead to significant data breaches and financial damage. Scaling these systems often calls for parallel processing infrastructures, efficient memory usage, and the adoption of hardware accelerators (e.g., GPUs or TPUs). Distributing both the training and inference processes across multiple nodes can accommodate continuously growing data volumes.

C. Regulatory and Ethical Aspects

Phishing URL detection tools often process personal data, such as email addresses or user metadata linked to browsing activity. Regulations such as the EU’s General Data Protection Regulation (GDPR) impose strict requirements on data handling and storage. Additionally, collecting large-scale URL datasets may raise questions about user privacy if logs contain sensitive user information.

Moreover, various jurisdictions have adopted their own laws to safeguard user data and hold organizations accountable for breaches. For instance, India introduced the Information Technology (IT) Act 2000 and subsequent amendments, which, along with the recently proposed Digital Personal Data Protection Bill, outline stringent data protection guidelines and penalties for misuse of personal information. Globally, other frameworks like the California Consumer Privacy Act (CCPA) in the United States and the General Data Protection Law (LGPD) in Brazil further highlight the international emphasis on regulating data collection and user privacy.

Federated learning approaches [?] represent one potential solution, allowing different entities to collaborate on model training without disclosing raw data. However, even federated methods can be vulnerable to privacy leakage if adversaries inject poisoned updates or if partial model parameters leak sensitive patterns. Hence, robust encryption and secure aggregation protocols remain an active area of research.

V. CONCLUSION

This review has traced the evolution of phishing URL detection methods, from traditional blacklist-based and heuristic systems to advanced techniques rooted in machine learning and deep learning. More recent large language model (LLM)**-based strategies provide notable improvements in capturing contextual and semantic details, though they bring their own challenges in terms of computational expense and interpretability. The incorporation of explainable AI addresses the critical need for transparency, enabling security analysts to interpret and trust model decisions in high-stakes environments. However, ongoing challenges such as adversarial attacks, scalability constraints, and data privacy concerns highlight the necessity for continuous innovation. Future work is likely to emphasize comprehensive, multi-layered solutions that integrate robust adversarial defenses, scalable real-time frameworks, and federated models to safeguard user data. By systematically merging these elements, the cybersecurity community can more effectively counter the persistent and evolving nature of phishing attacks.

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