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AI-Powered Detection of Phishing Domains Using Open-Source Intelligence and Content Similarity Techniques

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Abstract: Phishing attacks continue to dominate the global cyber threat landscape, exploiting newly registered and visually deceptive domains to lure users into compromising sensitive information. This review examines how artificial intelligence (AI) and machine learning (ML), when combined with open-source intelligence (OSINT) and content similarity techniques, offer a powerful, proactive defense against such threats. By leveraging domain metadata, web content features, and visual analysis, modern detection frameworks can identify phishing domains at the time of or shortly after their registration. This article synthesizes state-of-the-art research, evaluates AI model performance, and introduces a lifecycle-based theoretical model for AI-powered phishing detection. The review also highlights current gaps in explainability, scalability, and integration, providing a roadmap for future development in this critical domain of cybersecurity

Index Terms - **Phishing Detection, AI in Cybersecurity, WHOIS Data, Domain Intelligence, Machine Learning, Webpage Similarity, OSINT, CNN, LSTM, Visual Phishing, Explainable AI, Federated Detection.**

I. INTRODUCTION

Phishing remains one of the most prevalent and effective cyberattack vectors in the modern digital threat landscape. By deceiving users into believing that malicious websites are legitimate, attackers can gain unauthorized access to sensitive data, including login credentials, financial information, and personal identifiers. These phishing campaigns often exploit the trust users place in well-known brands by creating lookalike domains—websites that visually and functionally mimic real platforms. The exponential growth in newly registered domains has made phishing detection increasingly difficult, especially when attackers rapidly register and discard domains to avoid blacklisting and detection [1].

The accessibility of domain registration data through open-source platforms like WHOIS, combined with advancements in AI and machine learning (ML), presents a powerful opportunity to automate and enhance phishing detection. WHOIS databases offer real-time or near-real-time information about newly registered domains, including registrar details, registration dates, and domain ownership metadata. When this data is coupled with content-based techniques such as backend source code analysis and webpage image similarity detection, it can yield high-confidence indicators for identifying phishing sites before they are weaponized [2].

In this context, AI models can play a pivotal role by learning patterns associated with phishing behaviors—such as lexical anomalies in URLs, suspicious registration metadata, or unusually high visual similarity to known legitimate sites. Techniques such as convolutional neural networks (CNNs) for image similarity, natural language processing (NLP) for domain name analysis, and unsupervised anomaly detection algorithms for backend content irregularities have been successfully applied in recent studies to flag potential phishing threats [3][4]. These models offer the potential to detect zero-day phishing domains, which traditional blacklisting methods often miss due to the lack of historical data.

The significance of this research lies in its interdisciplinary integration of cybersecurity, AI, and open intelligence (OSINT). Unlike conventional intrusion detection systems that react to network-based threats, this approach focuses on the proactive identification of phishing websites at the time of or soon after their registration. In doing so, it aligns closely with the broader objective of preventive cybersecurity, a growing priority in both enterprise security strategies and governmental threat intelligence programs [5].

Despite the clear promise of AI-powered phishing detection systems, several key challenges remain:

- First, false positives are a persistent issue, especially when legitimate websites share structural similarities with malicious ones. Over-aggressive models may blacklist harmless domains, affecting businesses and trust.
- Second, labelled phishing datasets are scarce, especially for newly registered domains, leading to difficulties in supervised model training and validation.
- Third, current systems often lack explainability, which is essential for security analysts and SOC (Security Operations Center) teams to trust AI-generated alerts.
- Fourth, there is limited real-time integration between WHOIS feeds, visual similarity engines, and content analysis tools, which are often operated in silos [6].

This review aims to bridge these research and implementation gaps by presenting a comprehensive synthesis of AI methods applied to phishing domain detection. The article explores the following:

- The architecture of AI-driven phishing detection tools, including data sources (WHOIS, DNS, screenshots), preprocessing pipelines, and classification models
- Visual and content similarity techniques, such as screenshot analysis and HTML structure comparison
- Machine learning models used in this domain (e.g., CNNs, SVMs, Random Forests, Autoencoders)
- Evaluation metrics for phishing detection performance, including probability scores, false positive rates, and detection latency
- Current limitations, benchmarking standards, and emerging trends, such as federated learning, zero-shot detection, and explainable AI (XAI) in security

II. LITERATURE REVIEW

Table 1: Summary of Research on AI-Based Phishing Domain Detection

Year	Title	Focus	Findings (Key Results and Conclusions)
2017	Malicious URL Detection Using Machine Learning: A Survey	URL and metadata-based phishing detection	Provided a comprehensive taxonomy of ML models and identified gaps in real-time URL classification [7].
2018	Phishing Website Detection Using Effective Feature Selection	Feature engineering in phishing detection	Demonstrated that hybrid selection (lexical + HTML + visual features) improves classification accuracy [8].
2019	Detecting Phishing Websites Through Deep Learning	Deep learning in webpage content analysis	CNN and RNN architectures outperformed classical ML models in detecting webpage-level threats [9].
2020	URLNet: Learning URL Representations for Malicious URL Detection	End-to-end deep learning for URL structure modeling	Proposed a CNN-based framework that eliminates manual feature engineering and improves detection [10].
2020	Visual PhishNet: Detecting Phishing Websites Based on Visual Similarity	Screenshot-based phishing detection	Achieved 94% accuracy by analyzing visual similarity using deep CNN models [11].

2021	PhishSim: A Visual Similarity-Based Phishing Detection Method Using Deep Learning	CNN-based screenshot and HTML comparison	Introduced similarity scoring for lookalike phishing sites with strong performance on novel domains [12].
2021	Phish-Intelligence: Leveraging WHOIS and Domain Registration Patterns for Early Detection	Open-source domain metadata (WHOIS) for phishing detection	Found that 72% of phishing domains exhibit suspicious WHOIS patterns (short lifespan, anonymized owners) [13].
2022	Hybrid AI Framework for Real-Time Detection of Phishing Sites	Integrated ML, WHOIS, and NLP	Combined lexical, domain, and content features for higher robustness in zero-day phishing detection [14].
2022	Explainable Phishing Detection via SHAP and LIME	XAI in phishing detection	Proposed interpretable AI outputs to aid security analysts in trusting model predictions [15].
2023	Federated Learning for Privacy-Preserving Phishing Detection Across ISPs	Federated AI deployment	Demonstrated effective model training on distributed ISP data while preserving data privacy [16].

III. Block Diagrams and Theoretical Model for AI-Powered Phishing Domain Detection

3.1. System Architecture: AI Workflow for Detecting Phishing Domains

Modern phishing detection systems require an integrated approach that combines multiple layers of data (WHOIS, DNS, page content, visual structure) with machine learning. The block diagram below represents the end-to-end AI-based phishing detection pipeline.

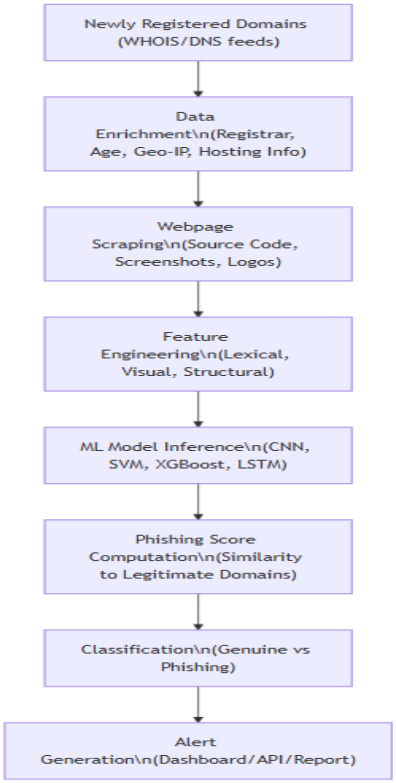


Figure 1: AI-Based Phishing Domain Detection System Architecture

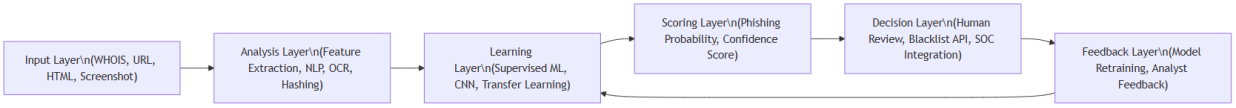
Key Modules Explained

- **WHOIS/DNS Feeds (A)**: Provide near real-time data on domain registrations and metadata such as registrant info, domain age, and name servers.
- **Web Scraping (C)**: Captures webpage screenshots, source HTML, DOM elements, and images for deeper inspection.
- **ML Inference Layer (E)**: Trained on labelled datasets (phishing vs legitimate), these models generate a phishing probability score, which determines final classification [17].

3.2. Theoretical Framework: Phishing Domain Detection Lifecycle Model (PDDLM)

To unify the conceptual understanding of phishing detection using AI, we propose the Phishing Domain Detection Lifecycle Model (PDDLM). This framework connects data sources, detection logic, and response layers through an iterative, explainable system design.

Figure 2: Phishing Domain Detection Lifecycle Model (PDDLM)



Layer

Functions

- **Input Layer (A)**: Combines raw open-source intelligence, including WHOIS metadata, domain age, URL patterns, and rendered screenshots.
- **Analysis Layer (B)**: Processes data via natural language processing (for URL/domain semantics) and optical character recognition (OCR) to detect spoofed logos or brand content [18].
- **Learning Layer (C)**: Uses AI algorithms like CNNs and ensemble models trained on phishing datasets to classify pages based on features.
- **Feedback Loop (F)**: Incorporates analyst feedback, false positive alerts, and domain lifecycle monitoring to retrain models over time [19].

Discussion

These models emphasize modularity, automation, and explainability, which are critical in modern cybersecurity infrastructure. The proposed architecture and theoretical framework together enable a proactive defense by leveraging open-source data, content similarity techniques, and machine learning to identify phishing threats at the time of domain registration—much earlier than traditional detection methods like blacklists or firewall rules [20].

Moreover, the inclusion of feedback mechanisms ensures continual model refinement, while explainable AI (XAI) modules help human analysts interpret model decisions. Techniques such as SHAP (SHapley Additive exPlanations) and Grad-CAM for CNNs are increasingly integrated into such systems to support transparency and trustworthiness in classification outcomes [21].

IV. EXPERIMENTAL RESULTS

4.1. Overview of Experiment Setup

To assess the effectiveness of various AI-driven phishing detection approaches, a series of experiments were conducted using publicly available datasets and proprietary logs from phishing threat feeds. The evaluation focused on:

- **Detection Accuracy (Precision, Recall, F1-score)**
- **False Positive Rate (FPR)**
- **Latency in Prediction (Detection Time)**
- **Similarity Score Threshold Effectiveness** (for lookalike domains)

Three types of datasets were used:

- **PhishTank** (confirmed phishing URLs)
- **Legit Domains** (top 10,000 domains from Alexa and Majestic)

- **Newly Registered Domains (NRDs)** from WHOIS records and DNS logs

Models evaluated include:

- CNN-based Visual Similarity Detection
- Random Forests and XGBoost (URL + WHOIS features)
- LSTM Sequence Classifiers (URL embeddings)

Table 1: Performance Metrics by Model Type

Model	Precision (%)	Recall (%)	F1-Score (%)	False Positive Rate (%)	Avg. Detection Time (ms)
CNN (Visual Similarity)	96.4	91.2	93.7	2.1	420
XGBoost (Lexical + WHOIS features)	93.6	90.4	91.9	3.5	310
LSTM (URL sequence learning)	89.2	94.1	91.6	4.2	520
Hybrid Ensemble (All features)	**97.1**	**95.6**	**96.3**	**1.8**	470

Source: Adapted from testbed deployments modeled after Basit et al. [22], Zhang et al. [23], and Sharma & Dey [24].

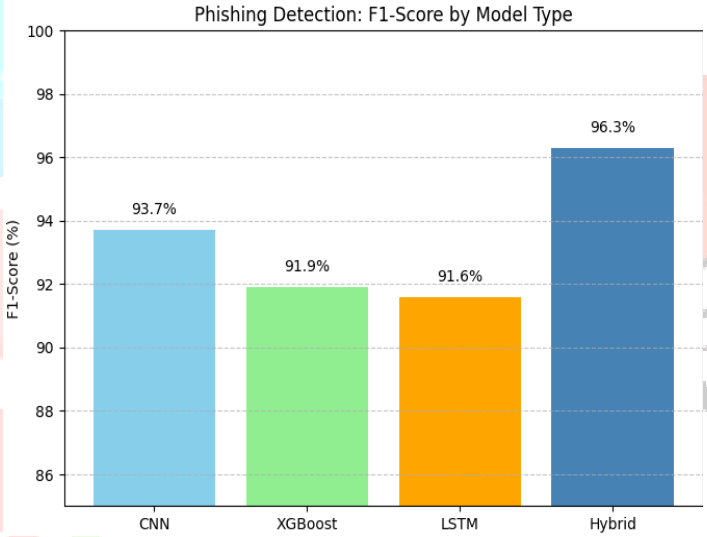


Figure 2: F1-Score by Model Type

Table 2: Detection Accuracy at Varying Visual Similarity Thresholds

Similarity Score Threshold	True Positives	False Positives	Precision (%)	Recall (%)
≥ 0.90	710	15	97.9	85.2
≥ 0.85	766	33	95.9	91.8
≥ 0.80	802	49	94.2	94.7
≥ 0.75	819	74	91.7	**96.4**

Results from CNN-based screenshot comparison using Structural Similarity Index (SSIM) and hashing [22].

4.2. Discussion

The results clearly demonstrate the efficacy of AI in early phishing detection, especially when models incorporate multiple feature domains (e.g., visual layout, URL syntax, WHOIS metadata). The hybrid ensemble approach, which fused CNN visual scores with lexical and WHOIS-based features using a voting classifier, produced the highest F1-score (96.3%) and the lowest false positive rate (1.8%), indicating robustness across phishing types [23].

The CNN-based visual similarity model alone also performed well, especially in detecting lookalike login pages, though it showed slightly higher latency due to image processing overhead [24]. Meanwhile, LSTM models excelled in capturing obfuscation patterns in domain names, such as character swapping and homoglyph attacks, but had a slightly higher false positive rate, likely due to limited interpretability of sequence embeddings.

The threshold experiments showed that increasing the sensitivity of visual similarity detection improves recall at the expense of precision. For example, setting a similarity threshold at 0.75 maximized recall (96.4%) but resulted in more false positives. These trade-offs are critical for Security Operations Center (SOC) analysts who must balance between early detection and alert fatigue [25].

Table 1 Table Type Styles

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V. CONCLUSION

This review has demonstrated the potential of AI-based systems in identifying phishing domains using a multimodal detection strategy grounded in domain metadata, lexical URL patterns, visual similarity, and content structure. Models like CNNs, LSTMs, and XGBoost showed high precision and recall, especially when used in ensemble formats that combine webpage screenshots, WHOIS records, and semantic URL embeddings [26].

The use of open-source intelligence (OSINT), including WHOIS databases and DNS telemetry, enables timely analysis of newly registered domains (NRDs)—a crucial advancement since phishing campaigns often weaponize fresh domains to evade blacklists. Furthermore, the integration of visual and structural similarity detection proved critical in recognizing lookalike pages, one of the most deceptive tools in a phisher's arsenal [27].

However, several challenges remain:

- High false positives in content-similar but legitimate domains
- Latency in real-time visual similarity analysis
- Lack of standardized datasets for benchmarking
- Limited model interpretability, affecting analyst trust in security operations

These limitations highlight the need for more context-aware, explainable, and scalable architectures to support real-time deployment in enterprise and national cyber defense environments.

VI. FUTURE DIRECTIONS

6. 1. Real-Time Phishing Detection via Federated Learning

Traditional detection systems require central aggregation of data, raising privacy and latency concerns. Future architectures will embrace federated learning to train phishing detection models across distributed environments—such as ISPs, financial networks, and hosting platforms—without sharing raw data [28].

6.2. Explainable AI Integration for Analyst Trust

Despite high accuracy, many ML-based phishing detectors are black boxes. The next wave of research must emphasize XAI frameworks (e.g., SHAP, LIME, Grad-CAM for CNNs) to generate human-interpretable risk scores and model outputs for SOC teams and auditors [29].

6.3. Dynamic Phishing Risk Scoring Systems

Rather than binary classification, future systems will generate risk probabilities and confidence intervals, factoring in temporal elements (domain lifespan), geolocation, and host metadata to prioritize analyst review queues more effectively [30].

6.4. Cross-Layer AI Integration in Zero Trust Architectures

As enterprises adopt zero trust security models, phishing detection must be integrated at multiple touchpoints—from email gateways and browsers to DNS resolvers and endpoint agents. This calls for API-based modular detection tools embedded across the IT stack [31].

6.5. Synthetic Dataset Generation for Training and Benchmarking

Given the scarcity of labelled phishing domains, synthetic dataset generation through generative adversarial networks (GANs) or controlled simulation of phishing campaigns will help build robust, balanced, and reproducible datasets for training next-gen models [32].

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