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Real-Time AI/ML-Based Phishing Detection and Prevention System

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Abstract:
Phishing attacks remain one of the most pervasive and economically devastating threats in the cybersecurity landscape, accounting for over 36% of all reported data breaches globally in 2024. This paper presents a novel real-time phishing detection and prevention system leveraging a hybrid ensemble of classical machine learning algorithms, deep learning architectures, and transformer-based natural language processing models. The proposed system integrates multi-modal feature extraction pipelines — encompassing URL structural analysis, domain reputation intelligence, HTML/JavaScript content inspection, and certificate transparency logs — to construct a rich, 287-dimensional feature vector for each candidate URL or email. An adaptive stacking ensemble combining XGBoost, LightGBM, Bi-LSTM, and a fine-tuned BERT variant achieves an accuracy of 99.6%, precision of 99.4%, and recall of 99.7% on a benchmark dataset of 2.8 million URLs. Real-time classification latency averages 89 milliseconds per sample, satisfying production-grade deployment requirements. We further introduce a continuously updating threat-intelligence feedback loop that allows the model to adapt to zero-day phishing campaigns without full retraining. Experimental results on three independent validation datasets outperform existing state-of-the-art baselines by 1.5–3.2 percentage points in F1-score.

Keywords *— phishing detection, machine learning, deep learning, BERT, ensemble methods, URL analysis, cybersecurity, real-time classification, transformer models, threat intelligence.*

I. Introduction

Phishing — the fraudulent practice of impersonating legitimate entities to harvest sensitive credentials, financial data, or install malware — has evolved dramatically in sophistication over the past decade. The Anti-Phishing Working Group (APWG) reported 5.1 million phishing attacks in 2024 alone, a 40% year-over-year increase, with estimated global financial losses exceeding $52 billion USD. Traditional rule-based and signature-driven detection systems have proven inadequate against polymorphic, adversarially crafted phishing pages that evade static blacklists within hours of deployment.

The emergence of artificial intelligence and machine learning has opened new frontiers in proactive cyber threat detection. Unlike static rule engines, ML-based systems can generalize from historical attack patterns to detect previously unseen variants, adapt continuously through online learning, and process high-dimensional feature spaces at sub-second latency. However, existing ML-based phishing detectors suffer from several limitations: high false-positive rates in enterprise environments, brittleness against adversarial URL perturbations, lack of real-time adaptability, and single-modality feature reliance.

This paper addresses these shortcomings by proposing PhishGuard-AI, a production-ready, real-time phishing

IV. Feature Engineering

A. URL Structural Features

Forty-seven features are extracted from the raw URL string, including total length, domain length, subdomain count, special character frequency (hyphens, underscores, at-signs), presence of IP addresses, port numbers, and hexadecimal encoding. Shannon entropy is computed over the full URL to capture obfuscation patterns commonly employed by adversaries. The top-level domain (TLD) is mapped to a risk-score lookup table derived from abuse.ch threat intelligence feeds.

B. Network and Domain Intelligence Features

Sixty-two features capture domain reputation and network infrastructure signals: WHOIS registration age, registrar risk score, DNS TTL anomalies, hosting ASN reputation, geographic hosting location mismatch relative to the claimed brand's headquarters, presence in threat intelligence feeds (AbuseIPDB, VirusTotal), and SSL certificate transparency log analysis. These features provide the strongest individual discriminative power, as phishing infrastructure typically exhibits short domain lifespans and low-reputation hosting providers.

C. Content and Visual Features

One hundred and twelve features are derived from page HTML and JavaScript: brand logo similarity via perceptual

detection and prevention system built upon a hybrid ensemble architecture. The key contributions of this work are:

- A 287-dimensional multi-modal feature extraction pipeline combining URL lexical, structural, network, content, and behavioral signals.
- A stacking ensemble of gradient-boosted trees (XGBoost, LightGBM), bidirectional LSTM, and a fine-tuned BERT-base transformer achieving 99.6% accuracy at 89ms average latency.
- An online learning feedback loop enabling zero-day phishing adaptation without full model retraining.
- Comprehensive evaluation across three independent benchmark datasets and adversarial perturbation stress tests.
- An open-source reference implementation compatible with browser extension, email gateway, and REST API deployment paradigms.

The remainder of this paper is structured as follows: Section 2 reviews related work; Section 3 details the system architecture; Section 4 describes the feature engineering methodology; Section 5 presents the ensemble learning framework; Section 6 reports experimental results; Section 7 discusses deployment considerations; Section 8 concludes and outlines future directions.

II. Related Work

A. Rule-Based and Blacklist Approaches

Early phishing detection relied heavily on manually curated blacklists maintained by organizations such as Google Safe Browsing, PhishTank, and OpenPhish. While effective for known threats, blacklist-based systems exhibit inherent latency — newly deployed phishing pages can remain active for 4–8 hours before appearing on blocklists (Moore & Clayton, 2007). SURBL and URIBL extended this paradigm by incorporating spam URI reputation databases, but remained reactive rather than proactive.

B. Classical Machine Learning Methods

Garera et al. (2007) pioneered the use of logistic regression on URL-derived features, achieving approximately 95.7% accuracy on a dataset of 1,000 URLs. Subsequent work by Ma et al. (2009) employed online learning with lexical and host-based features, demonstrating scalability to millions of URLs. Support Vector Machines (Basnet et al., 2012) and Random Forests (Tan et al., 2018) further improved performance, with the latter achieving 97.8% accuracy by combining 30 URL and page-content features. However, classical approaches struggled with feature engineering overhead and adversarial robustness.

C. Deep Learning Approaches

Convolutional Neural Networks applied to raw URL character sequences were proposed by Le et al. (2018), hashing, external resource ratio, form action domain mismatch, hidden iframe count, JavaScript obfuscation score, meta-refresh redirect presence, and favicon domain consistency. A lightweight ResNet-18 model pretrained on a 500,000-image phishing screenshot dataset produces a 128-dimensional visual embedding capturing the page's overall layout similarity to known legitimate brand pages.

D. Transformer Semantic Embeddings

A BERT-base model fine-tuned on a combined corpus of 1.2 million phishing and legitimate URL tokens produces a 66-dimensional semantic embedding (projected from 768 via PCA). This embedding captures lexical patterns imperceptible to classical feature engineering, such as brand name misspellings, homoglyph substitutions (e.g., 'rn' for 'm'), and deceptive subdomain structures. Table I summarizes the top seven features by SHAP-derived importance score.

TABLE I
FEATURE IMPORTANCE ANALYSIS (SHAP VALUES, TOP 7 FEATURES)

#	Feature	Score	Impact
1	URL Length & Structure Entropy	0.231	Very High
2	Domain Age & WHOIS Anomaly Score	0.198	Very High
3	SSL Certificate Validity	0.172	High
4	Lexical URL Token Frequency	0.154	High
5	Page Content Similarity (TF-IDF)	0.119	Moderate
6	Redirect Chain Depth	0.087	Moderate
7	IP Geolocation Mismatch	0.039	Low

V. Ensemble Learning Framework

A. Base Learners

Four base learners constitute the first layer of the stacking ensemble. XGBoost (v1.7) is configured with 800 trees, max depth 8, learning rate 0.05, and subsample ratio 0.8. LightGBM employs leaf-wise growth with 1,200 leaves and feature fraction 0.7. The Bidirectional LSTM processes URL token sequences of length 128 with two 256-unit hidden layers and 0.3 dropout. The fine-tuned BERT model uses a [CLS] token classification head with two fully connected layers (768→256→2).

B. Meta-Learner

A logistic regression meta-learner with L2 regularization (C=1.0) combines the probability outputs of all four base learners along with the raw 287-dimensional feature vector as additional meta-features. This design allows the meta-learner to learn which base model to trust for specific feature profiles — for instance, weighting XGBoost higher for URL-structural signals while relying on BERT for brand-impersonation semantics. Five-fold cross-validation was used to generate out-of-fold predictions for meta-learner training, preventing target leakage.

eliminating manual feature engineering while achieving 98.2% accuracy. Yang et al. (2019) employed attention-based LSTM networks to capture sequential URL token dependencies. More recently, transformer-based models pre-trained on large text corpora have been fine-tuned for phishing URL classification. Abdelnabi et al. (2020) demonstrated that BERT-based models can detect typosquatting and brand impersonation attacks with high sensitivity. Despite strong performance, these models are computationally expensive and often lack real-time capability.

D. Hybrid and Ensemble Methods

Recognizing the complementary strengths of classical and deep learning approaches, several ensemble architectures have been proposed. Vrbancic et al. (2020) combined Random Forest with an autoencoder for anomaly detection, achieving 98.9% F1-score. Zouina & Outtaj (2017) proposed stacked generalization with five base classifiers. Our work extends this paradigm by integrating transformer-derived semantic embeddings as additional meta-features in the stacking layer, a combination not previously explored in the phishing detection literature.

III. System Architecture

A. Overview

PhishGuard-AI follows a five-stage pipeline architecture: (1) Input Ingestion, (2) Multi-Modal Feature Extraction, (3) Base Model Inference, (4) Ensemble Aggregation, and (5) Response & Feedback. The system is designed as a microservices-based architecture deployable on cloud infrastructure (AWS, GCP, Azure) or on-premises data centers, with horizontal scaling support for high-throughput environments.

B. Input Ingestion Layer

The ingestion layer accepts inputs from three primary channels: (a) browser extension HTTP intercepts capturing navigated URLs in real time, (b) email gateway MIME parsing for link extraction from HTML and plain-text emails, and (c) a RESTful API endpoint for third-party integration. All inputs are normalized to a canonical (URL, raw_html, timestamp) triple before entering the feature extraction pipeline. Rate limiting and circuit breaker patterns are implemented to ensure service stability under load spikes.

C. Feature Extraction Pipeline

The feature extraction module operates as a parallel computation graph with four independent sub-pipelines whose outputs are concatenated into the final feature vector. DNS lookups and WHOIS queries are cached with a 24-hour TTL to minimize latency. Asynchronous I/O ensures that network-bound operations do not block CPU-bound feature computations.

C. Online Adaptation Module

A sliding-window incremental learning module continuously retrains the XGBoost and LightGBM base learners on new confirmed phishing samples reported via the browser extension feedback button or security analyst labeling queue. Retraining is triggered when the sliding window accumulates 500 new labeled samples, takes approximately 4.2 minutes on a 16-core CPU server, and is deployed with zero downtime via model version management and A/B traffic splitting.

VI. Experimental Results

A. Datasets

Three datasets were used for evaluation. The Primary Dataset comprises 2.8 million URLs (1.4M phishing, 1.4M legitimate) sourced from PhishTank, OpenPhish, Alexa Top-1M, and DMOZ. The Adversarial Dataset contains 85,000 adversarially perturbed phishing URLs crafted using homoglyph substitution, URL shortening, and subdomain cloaking. The Zero-Day Dataset consists of 12,000 phishing URLs active for less than 24 hours, collected via CERT feeds to evaluate temporal generalization.

B. Baseline Comparisons

PhishGuard-AI is compared against five baselines: Random Forest (Tan et al., 2018), XGBoost (standalone), LSTM-based classifier (Yang et al., 2019), Transformer-only (BERT fine-tuned, Abdelnabi et al., 2020), and the strongest published ensemble (Vrbancic et al., 2020). All models are retrained and evaluated on identical data splits for fair comparison. Table II reports performance on the Primary Dataset.

TABLE II
Performance Comparison on Primary Dataset (2.8M URLs)

Model	Accuracy	Precision	Recall	Latency
Random Forest	97.2%	96.8%	97.4%	23ms
XGBoost	98.1%	97.9%	98.3%	31ms
LSTM (Deep)	98.7%	98.5%	98.9%	67ms
Transformer	99.1%	98.8%	99.3%	112ms
Proposed Ensemble	99.6%	99.4%	99.7%	89ms

C. Adversarial Robustness

On the Adversarial Dataset, PhishGuard-AI maintains 96.8% accuracy, compared to 88.2% for standalone BERT and 82.4% for Random Forest. The multi-modal feature integration provides robustness to URL-level perturbations because network, content, and visual features remain largely unaffected by character-level URL manipulations. The online adaptation module further recovers 1.4% accuracy within 48 hours of adversarial campaign exposure through confirmed-sample feedback.

D. Model Serving Infrastructure

Base models are served via ONNX Runtime for hardware-accelerated inference across CPU and GPU deployments. The BERT model employs TensorRT optimization and INT8 quantization, reducing inference time from 380ms to 112ms while sacrificing less than 0.3% accuracy. A Redis-backed prediction cache stores recent inference results for repeated URL queries, achieving a cache hit rate of 34% in production traffic analysis, effectively reducing average system latency to 58ms for cached requests.

D. Zero-Day Detection Performance

On the Zero-Day Dataset, the proposed system achieves 93.7% accuracy, demonstrating strong temporal generalization. Domain-age and SSL transparency features contribute most significantly to zero-day performance, as newly registered phishing infrastructure consistently exhibits anomalous patterns regardless of URL camouflage quality. The online learning module is shown to reduce zero-day false-negative rate by 23.1% after one week of deployment in a monitored enterprise environment.

VII. Deployment Considerations

A. Browser Extension Integration

The browser extension intercepts HTTP navigation events via the webNavigation API and submits URLs to a local lightweight proxy (100ms timeout) before page rendering. A lightweight on-device XGBoost model (2.3MB) serves as a first-pass filter, forwarding only uncertain predictions (confidence 0.3–0.7) to the full cloud ensemble. This tiered architecture reduces cloud API calls by 61% while maintaining end-to-end detection latency under 150ms for 94% of requests.

B. Email Gateway Deployment

Integration with enterprise email gateways (Microsoft Exchange, Postfix, Sendmail) is achieved via SMTP milter hooks. All hyperlinks within incoming emails are extracted, deduplicated, and submitted in parallel to the PhishGuard-AI API before message delivery. Emails containing links classified as phishing are quarantined and replaced with a sanitized notification, and the original message is preserved for security analyst review. Average processing overhead adds 340ms to email delivery latency, within acceptable bounds for enterprise deployment.

C. Privacy and Compliance

All URL submissions are hashed using SHA-256 before transmission to the cloud API, ensuring that raw browsing history is never stored on remote servers. GDPR and CCPA compliance is maintained through data minimization, explicit user consent mechanisms in the browser extension onboarding flow, and automated 30-day data purge policies for all processed records. An on-premises deployment option is available for organizations with strict data sovereignty requirements.

VIII. Conclusions

This paper presented PhishGuard-AI, a real-time AI/ML-based phishing detection and prevention system incorporating a novel hybrid ensemble of gradient-boosted trees, bidirectional LSTM, and BERT-based transformer models over a rich 287-dimensional multi-modal feature space. Extensive

experimental evaluation demonstrates state-of-the-art performance (99.6% accuracy, 99.7% recall) on a 2.8 million URL benchmark dataset, with strong adversarial robustness and zero-day generalization capabilities. The system's real-time inference latency of 89ms and continuous online learning adaptation make it suitable for production deployment across browser extension, email gateway, and API integration paradigms.

Future work will explore federated learning to enable privacy-preserving collaborative model improvement across enterprise deployments without centralizing sensitive URL data. Additionally, graph neural networks applied to phishing campaign infrastructure clustering present a promising direction for proactive takedown intelligence. We will also investigate multi-lingual phishing detection targeting non-English brand impersonation campaigns, which currently constitute an underserved threat category in the academic literature.

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