Real-Time Phishing URL Detection Using Fine-Tuned DistilRoBERTa

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Dr. D. Sakthivel
Assistant Professor, Department of Computer Technology
KG College of Arts and Science, Coimbatore, Tamil Nadu, India

Abstract
The widespread adoption of internet-based services has led to a substantial rise in phishing attacks, which constitute a major threat to both user privacy and the broader cybersecurity landscape. Attackers craft malicious URLs to manipulate users into disclosing confidential information—including login credentials, banking details, and personal identifiers—ultimately resulting in financial harm and identity compromise. Conventional detection strategies, such as static blocklist-based filtering and rule-driven feature engineering, are inherently insufficient for countering dynamically generated or previously unseen (zero-day) phishing URLs. To address these shortcomings, this study introduces a real-time phishing URL detection framework built upon DistilRoBERTa, a computationally lean transformer model derived from RoBERTa. The system treats each URL as a raw text sequence and applies Byte Pair Encoding (BPE) tokenization to extract both lexical and structural cues. Through fine-tuning DistilRoBERTa with an attached classification head, the model autonomously acquires contextual relationships between URL components, removing any dependency on manually engineered features. The framework is specifically architected to function on standard CPU-only hardware, making it viable for real-world deployment scenarios. Experiments were conducted on a curated benchmark dataset comprising 12,000 labeled URLs, partitioned into training and test subsets. Model effectiveness was measured using Accuracy, Precision, Recall, F1-score, ROC-AUC, and confusion matrix analysis. The results confirm strong detection performance—an accuracy of 90.55%, recall of 98.61%, and F1-score of 92.30%—demonstrating the model's capacity to reliably identify phishing URLs while keeping false negatives to a minimum. Benchmarking against classical machine learning models, deep neural architectures, and the full RoBERTa model reveals that DistilRoBERTa achieves an advantageous balance between detection efficacy and runtime efficiency. Real-time inference experiments further validate the system's readiness for deployment in browser security extensions, intrusion detection pipelines, and network monitoring infrastructures.

Keywords: Phishing URL Detection, DistilRoBERTa, Transformer Models, Real-Time Security, Byte Pair Encoding, Deep Learning, Cybersecurity, URL Classification, Contextual Feature Learning, Anomaly Detection

Introduction

The exponential growth of online platforms has transformed how people communicate, conduct commerce, and access information. However, this digital expansion has simultaneously amplified the attack surface for cybercriminals, with phishing representing one of the most pervasive and economically damaging threat categories. Phishing URLs are strategically crafted to impersonate trusted entities, deceiving users into voluntarily submitting sensitive data. The downstream consequences include financial losses, identity theft, and reputational damage for both individuals and organizations.

Existing countermeasures—such as static blocklists and signature-based rule engines—fail to keep pace with the adaptability of modern phishing campaigns. Adversaries continuously mutate URL structures to circumvent these filters, rendering them obsolete shortly after deployment. While machine learning techniques have demonstrated promise in automating phishing detection, many classical approaches demand extensive domain-specific feature engineering, creating scalability and maintenance challenges. Transformer-based language models such as RoBERTa represent a paradigm shift, enabling the autonomous learning of contextual patterns directly from raw text. Nevertheless, their substantial computational footprint has historically impeded integration into latency-sensitive, real-time security systems.

This work proposes a phishing URL detection architecture centered on DistilRoBERTa—a distilled, parameter-efficient derivative of RoBERTa—to bridge the gap between detection capability and operational feasibility. By encoding URLs as token sequences and utilizing BPE tokenization, the proposed system captures nuanced lexical and structural features characteristic of malicious URLs without manual intervention. The paper is organized as follows: Section II reviews prior work, Section III describes the proposed methodology, Section IV presents experimental outcomes, Section V benchmarks the model against existing approaches, and Section VI concludes with a discussion of future research avenues.

Review of Literature

Research into automated phishing URL detection has evolved through several distinct technological phases. Initial efforts in this domain relied heavily on manually curated feature sets, including lexical indicators (such as URL length, token counts, and special character ratios) and host-based attributes, paired with conventional classifiers like Support Vector Machines, Random Forests, and Logistic Regression. While these approaches established a useful baseline, their reliance on fixed feature definitions limited generalization capacity and imposed significant ongoing engineering overhead.

The emergence of deep learning introduced character-level and sequence-based models—including Convolutional Neural Networks and Long Short-Term Memory networks—capable of learning URL representations from raw input without explicit feature design. These architectures improved detection rates considerably but were constrained in their ability to model non-local dependencies within URLs due to their inherently local receptive fields or sequential processing nature.

The introduction of attention-based transformer architectures, including BERT and RoBERTa, marked a significant advancement in the field. These models leverage self-attention mechanisms to simultaneously model relationships across the entire input sequence, yielding richer contextual representations and substantially improved classification performance. Their primary limitation, however, is high computational and memory demand, which creates barriers for integration into real-time or resource-constrained environments.

Distilled model variants such as DistilRoBERTa—developed through knowledge distillation from larger teacher models—retain a high proportion of the parent model's representational power while achieving meaningful reductions in parameter count and inference latency. This characteristic makes DistilRoBERTa a compelling candidate for real-time security applications, motivating the present research.

Proposed Methodology

The proposed framework for real-time phishing URL detection is built around a fine-tuned DistilRoBERTa transformer model. The fundamental premise is to enable the automatic extraction of contextual and structural patterns from URLs, bypassing the need for manually crafted feature sets. The system is architected for computational efficiency and is intended for deployment in time-critical cybersecurity contexts.

The end-to-end processing pipeline consists of four principal stages: (1) URL preprocessing, (2) BPE tokenization, (3) contextual representation learning via DistilRoBERTa, and (4) binary classification. Each stage is described in detail in the subsections below.

System Architecture

The architecture begins by accepting a raw URL string as input. The URL undergoes normalization to remove noise, followed by tokenization using BPE to convert it into a sequence of subword units. These token embeddings are passed through the DistilRoBERTa encoder, which produces a contextualized representation. A fully connected classification head then maps this representation to a binary output—phishing or legitimate—along with an associated confidence score.

Algorithm: ContextAware_Phishing_Detection

The proposed algorithm operates at the token level, learning contextual dependencies among URL components to distinguish phishing from legitimate URLs. The notation used in the algorithm is defined in Table I.

Table 1 Symbol Definitions for the Proposed Algorithm

Symbol	Meaning
X	Input URL string
X’	Preprocessed URL
T	Token sequence
K	Token index (position)
Ek	Embedding vector at position K
H	Contextual representation from encoder
W	Trainable weight matrix
$\hat{Y}$	Predicted label (0 = Legitimate, 1 = Phishing)
Y	Ground-truth label

Algorithm Listing — ContextAware_Phishing_Detection
Input: URL string X
Output: Predicted label $\hat{Y}$, Probability score P
Begin
Step 1 — Preprocessing:
X’ ← Normalize(X)
Step 2 — Tokenization:
T ← Tokenize(X’)
Step 3 — Embedding:
For each token position K in T:
E_k ← Embedding(T_k) End For
Step 4 — Context Learning:
H ← DistilRoBERTa(E_1, E_2, ..., E_n)
Step 5 — Classification:
Z ← W · H; P ← Softmax(Z)
Step 6 — Decision Rule:
If P[1] >= 0.5:
$\hat{Y}$ ← 1 (Phishing)
Else:
$\hat{Y}$ ← 0 (Legitimate)
Return $\hat{Y}$, P
End

Key strengths of this algorithmic design include: elimination of handcrafted feature extraction, capture of contextual token-level dependencies, accelerated training and inference enabled by the distilled architecture, robustness against obfuscated and newly emerging phishing patterns, and suitability for CPU-only real-time deployment.

Experimental Results and Analysis

Experimental Setup

The experimental pipeline follows four sequential phases: dataset preparation, tokenization, model fine-tuning, and performance evaluation.

Dataset Preparation: The study uses a labeled phishing URL dataset sourced from the UCI Machine Learning Repository, containing URLs annotated as either phishing or legitimate. To ensure evaluation integrity, the dataset is partitioned into 10,000 URLs for model training and 2,000 URLs for testing. This split prevents data leakage and provides a fair assessment of the model's ability to generalize beyond its training distribution.

Tokenization: Each URL is processed as a text sequence using the DistilRoBERTa tokenizer, which applies BPE to segment URLs into subword units. This decomposition allows the model to identify suspicious patterns such as misleading domain fragments, irregular character sequences, and structural manipulations that are characteristic of phishing URLs.

Model Training: A binary classification head is appended to the DistilRoBERTa encoder and the entire model is fine-tuned end-to-end. The training objective is cross-entropy loss, and parameter updates are performed using the AdamW optimizer, which incorporates decoupled weight decay to enhance convergence stability. All training is performed on a standard CPU to validate deployment viability in resource-constrained settings.

Implementation Environment: All experiments are implemented in Python 3.13, using the Hugging Face Transformers library and PyTorch as the underlying deep learning framework. The exclusive use of CPU hardware underscores the practical accessibility of the proposed system for environments lacking dedicated accelerators.

Evaluation Metrics

A comprehensive suite of metrics is employed to measure model performance across multiple dimensions:

- **Accuracy:** Proportion of correctly classified samples across all URL instances.
- **Precision:** Fraction of flagged URLs that are genuinely malicious, reflecting false positive control.
- **Recall:** Fraction of actual phishing URLs correctly identified, measuring sensitivity to malicious content.
- **F1-Score:** Harmonic mean of Precision and Recall, offering a balanced composite performance measure.
- **ROC-AUC:** Area under the Receiver Operating Characteristic curve, assessing discrimination ability across decision thresholds.
- **Confusion Matrix:** Full tabulation of true positives, true negatives, false positives, and false negatives.

Quantitative Results

The test-set performance metrics for the proposed DistilRoBERTa-based detector are reported below:

Table 2 Performance Metrics on the Test Dataset

Metric	Score
Accuracy	90.55%
Precision	86.74%
Recall	98.61%
F1-Score	92.30%
ROC-AUC	93.60%

These metrics collectively affirm the effectiveness of the proposed approach. The exceptionally high recall value (98.61%) is particularly significant in a security context, as it indicates that nearly all phishing URLs in the test set are successfully flagged—minimizing the risk of undetected attacks that could lead to user harm. While precision is slightly lower, this trade-off is generally acceptable in threat detection systems where missing a genuine attack carries greater cost than issuing a false alarm.

Confusion Matrix Analysis

The confusion matrix reveals that a very small proportion of phishing URLs are misclassified as legitimate (false negatives), confirming the model's high sensitivity. A limited number of benign URLs are incorrectly labeled as phishing (false positives), a trade-off that is acceptable—and often preferred—in security-critical applications where the primary imperative is to detect and neutralize threats. Figure 4.1 presents the confusion matrix visualization, and Figure 4.2 illustrates the ROC curve.

Real-Time Inference Analysis

To evaluate operational readiness, the trained model is embedded within an interactive URL classification interface. Representative inference outputs are shown below:

Table 3 Sample Real-Time Inference Results

Input URL	Prediction	Confidence
https://www.bayhilljewelers.com	Phishing	90.82%
https://www.neurosurgeon.org	Phishing	97.18%
https://recaptcha-8325.firebaseapp.com/	Legitimate	0.10%

These inference examples demonstrate that the system is capable of delivering accurate, high-confidence classifications in real time. The results support deployment within browser security extensions, enterprise security gateways, and network-level intrusion detection systems.

Comparison with Existing Models

To rigorously benchmark the proposed system, its performance is evaluated against a representative selection of established machine learning, deep learning, and transformer-based approaches. All models are assessed on an identical test dataset using the same evaluation protocol.

Table 4 Comparative Performance of Phishing URL Detection Models

Model	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	83.10%	80.50%	85.20%	82.77%	88.30%
Random Forest	85.70%	83.40%	87.90%	85.59%	90.10%
SVM	84.30%	81.60%	86.40%	83.93%	89.50%
CNN	87.50%	84.90%	90.10%	87.42%	91.60%
LSTM	88.10%	85.70%	91.30%	88.41%	92.30%
BERT	89.40%	86.90%	93.20%	89.94%	93.10%
RoBERTa	91.20%	88.70%	95.50%	91.97%	94.80%
Proposed (DistilRoBERTa)	90.55%	86.74%	98.61%	92.30%	93.60%

The comparative analysis reveals that the proposed DistilRoBERTa model achieves the highest recall among all evaluated models—a critical metric for security systems. While the full RoBERTa model edges ahead on accuracy and precision, DistilRoBERTa delivers comparable overall performance at a fraction of the computational cost, making it a pragmatically superior choice for deployment in real-time, resource-limited environments.

Conclusion and Future Work

This paper has presented a real-time phishing URL detection system leveraging a fine-tuned DistilRoBERTa model. By encoding URLs as raw token sequences and exploiting transformer-based contextual learning, the proposed framework successfully captures lexical, syntactic, and structural signatures of phishing URLs without dependence on manual feature engineering. The distilled architecture ensures efficient computation on standard CPUs, making the system broadly applicable in resource-constrained deployment environments.

The experimental evaluation confirms strong detection performance, achieving 90.55% accuracy, 92.30% F1-score, and 93.60% ROC-AUC. The model's exceptional recall of 98.61% underlines its reliability in identifying phishing threats, which is the primary objective in cybersecurity applications. Comparative experiments validate that DistilRoBERTa achieves a favorable trade-off between detection robustness and operational efficiency relative to both classical and more computationally intensive transformer models.

Several directions for future research are identified. First, the detection framework could be extended to incorporate multimodal inputs, including webpage HTML structure, rendered visual content, and network-level traffic features, to further strengthen detection robustness. Second, continual learning strategies could be integrated to allow the model to incrementally adapt to emerging phishing campaigns without requiring full retraining. Third, deployment as a browser extension or network security middleware, coupled with comprehensive latency profiling and energy consumption benchmarking, would provide critical insights into scalability for large-scale production use.

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