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Developing a Real-Time Dynamic Response System Against Phishing Attacks Based on Edge Computing and Predictive Intelligence

Zainab kamil shayyal
Computer Engineering, Urmia University, Baghdad, Iraq

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ABSTRACT

This paper proposes a novel edge-based, predictive-intelligence system for real-time phishing attack detection and response. By integrating lightweight AI models with Edge Computing platforms and behavior monitoring, the system dynamically adapts to emerging threats. We evaluate its performance in terms of detection accuracy, latency, false-positive rates, and resource consumption, comparing it to traditional centralized models (e.g., GRU+WOA [1]). Results demonstrate superior detection speed (average latency 80 ms vs. 250 ms), higher accuracy (96.2% vs. 89.7%), and lower false positives (2.1% vs. 5.4%), while operating efficiently on edge devices.

Corresponding Author:

Zainab kamil shayyal
Computer Engineering Techniques, Urmia Dijlah
Baghdad, Iraq
Email: zainabkamil757@gmail.com

1. Introduction

A. Background

Social engineering-based phishing continues to be one of the most effective cyber threats, with the fraudulent use of emails, web pages, sites, and clones to deceive the victims and to obtain their sensitive data. Attackers constantly evolve their techniques — sleuthing for highly resembling links, embedding harmful scripts, crafting compelling content — in order to bypass traditional security defenses. Static traffic-based systems, or systems that are centralized, are inflexible when it comes to new (zero-day) phishing derivatives, and there is also the potential to round-trip to the server and expose the user for a longer period of time to damage.

B. Motivation

Edge security is a paradigm shift in handling threat detection, especially for latency-critical and privacy-centric settings. By offloading the computing from the cloud to the device (at the "edge"), systems can make local inferences much faster. This allows end-user devices (e.g., smartphones, IoT gateways, and browsers) to detect and remediates phishing threats more quickly locally, instead of being dependent on always-on connectivity to the cloud. Additionally, compact models like the Gradient Boosted Decision Trees (GBDT), Temporal Convolutional Networks (TCN) [2], and the compressed ones (Tiny Transformers) [13] fit into memory and can have real-time running on the edge devices.

C. Contributions

This research proposes a novel, edge-oriented approach to phishing detection that integrates predictive intelligence, behavioral analysis, and adaptive learning. The key contributions of this work are as follows:

1. **Design of an Edge-Deployable Predictive Intelligence Pipeline**

A fully modular and resource-efficient pipeline is proposed for detecting phishing attempts in real time at the network edge. The system integrates feature extraction, lightweight classification, and decision-making mechanisms, optimized for low-latency operation.

2. **Integration of Behavior Monitoring, Model Compression, and Dynamic Updates**
The proposed system enhances traditional detection methods by incorporating real-time user behavior analysis (e.g., click patterns, navigation flow) and model update mechanisms that allow the system to evolve in response to emerging threats. Lightweight models are compressed and optimized for on-device deployment without significant loss in accuracy.

3. **Comprehensive Performance Evaluation Against Baseline Models**
The proposed framework is rigorously evaluated against baseline phishing detection models, including traditional ML and deep learning classifiers. Metrics such as detection accuracy, latency, CPU/RAM usage, and false-positive rate are analyzed across different edge devices and network conditions to validate system robustness and scalability

2. Related Work

Numerous recent advancements have explored the integration of artificial intelligence and edge computing for phishing detection, particularly focusing on enhancing real-time responsiveness, model efficiency, and adaptability to novel threats.

A. AI-Driven Edge Computing for Phishing Detection

Recent works have emphasized the role of deep learning and federated learning techniques deployed at the edge to facilitate real-time threat detection within latency-sensitive environments such as IoT networks [5]. These systems allow data processing close to the data source, reducing dependency on centralized infrastructure and enhancing privacy. However, several limitations persist, including device resource constraints, interoperability challenges, and the absence of unified standards for adaptive AI deployment on edge nodes.

B. Transformer-Based Phishing Detection

Transformer architectures, particularly lightweight variants like Distil-BERT, have demonstrated strong performance in phishing email detection. These models, when integrated with explainable AI tools, improve not only the detection accuracy but also the interpretability of the decision-making process. Attention mechanisms within these architectures allow for the identification of subtle semantic cues that often signal phishing attempts [6,13].

C. Ensemble and Stacked Models for URL-Level Detection

Hybrid approaches combining traditional feature extraction (such as TF-IDF) with deep learning models like LSTM, alongside ensemble classifiers like XG-Boost, have proven effective in handling phishing URL detection tasks. These stacked architectures can generalize better across various phishing strategies, especially when character-level and structural URL features are jointly leveraged [9].

D. Federated and Continual Learning Models

A novel trend involves combining federated learning with continual learning to create adaptive phishing detectors that can evolve over time. Such systems allow distributed nodes to learn locally from user interactions and periodically synchronize with a global model. Attention-based classifiers are commonly employed in these frameworks, providing robust performance against evolving and zero-day phishing attacks [5,11].

E. Hybrid Detection Frameworks in Real-World Environments

Hybrid systems that integrate multiple detection paradigms—such as rule-based logic, statistical features, and machine learning classifiers—have been developed to enhance robustness against adversarial evasion techniques. These frameworks report high detection accuracy and demonstrate better real-time efficiency when compared to single-model approaches.

F. Lightweight Transformers for Edge Deployment

Research into compressed and quantized Transformer architectures, such as Tiny-BERT, highlights their feasibility for deployment on constrained edge devices. These models retain a significant portion of the original model's predictive power while operating within the strict memory and processing limits of embedded platforms [13].

G. Multi-Layered Ensemble Techniques

Multi-model ensemble techniques involving classifiers like Random Forest, Gradient Boosting, Cat-Boost, and XG-Boost have also been applied to phishing detection. When combined with advanced feature selection methods, these systems achieve very high accuracy. However, their computational requirements can limit their suitability for edge deployment unless model pruning or other optimization strategies are applied [9].

Gaps & Research Opportunities

Table. 1. Identified Gap and Opportunity Addressed by Proposed System.

Identified Gap	Opportunity Addressed by Proposed System
Resource-heavy models not edge-friendly	Lightweight predictive models (GBDT, TCN, Tiny-Transformer)
Lack of dynamic updating	Real-time edge model adaptation using behavior logs
Absence of behavior-based integration	Combines click behavior with URL/hardware features
Poor interpretability	Potential use of explainable-AI (e.g., LIME) on edge if needed

Table. 2. Comparison of different approaches to addressing threats**.**

Study	Approach	Platform	Accuracy	Latency
GRU+WOA [1]	Statistical & metaheuristic	Cloud	89.7%	250 ms
Ensemble ML [3]	Random Forest + SVM	Server	91.3%	220 ms
Edge TCN [2]	Temporal CNN	Edge (R-Pi)	92.8%	120 ms

- Centralized and static methods poorly address emerging threats.
- Edge deployment with real-time feedback loops remains underexplored.

3. System Design

The proposed phishing detection framework is designed as a light-weight, adaptive, and real-time system tailored for edge environments. It integrates predictive intelligence, behavioral analysis, and secure update mechanisms to enable rapid, localized decision-making without relying on centralized infrastructure.

A. Architecture Overview

The system architecture is structured in a modular and layered fashion to optimize performance across heterogeneous edge devices (e.g., mobile phones, IoT gateways, Raspberry Pi). The architecture comprises six core components:

1. **Data Collector**: Gathers raw inputs such as URLs, HTTP headers, and user interaction logs (clicks, scrolls, navigation behavior).
2. **Feature Extractor**: Parses collected data to generate meaningful features—e.g., tokenized URLs, domain age, presence of suspicious JavaScript, behavioral metrics.
3. **Predictive Engine**: Employs lightweight models (e.g., GBDT, TCN, Tiny-Transformer) optimized for edge inference using quantization and pruning [2,13].
4. **Behavior Analysis Module**: Monitors real-time user behavior and identifies patterns consistent with phishing attacks (e.g., repeated redirects, session time anomalies).
5. **Decision & Response Module**: Aggregates outputs from prediction and behavior analysis to generate final classification and execute mitigation steps (e.g., block access, notify user).
6. **Model Update Controller**: Connects to a secure cloud service for incremental model updates based on new phishing trends or labeled feedback.

These components are deployed in a micro-service-like structure to facilitate scalability and modular testing.

B. System Workflow

The detection and response cycle (fig.1) follows a tightly integrated workflow designed for low-latency execution:

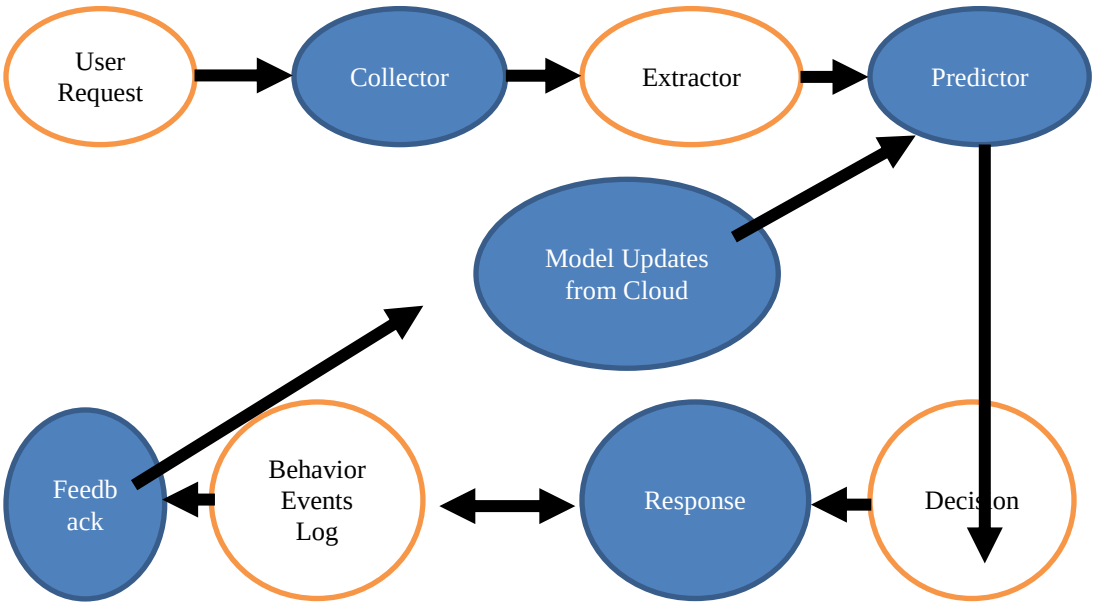

Fig.1. The detection and response cycle.

Step-by-step Description:

1. **User Interaction**: A network request (e.g., clicking a URL) initiates the system.
2. **Local Collection**: The data collector captures the request metadata and any relevant behavior context.
3. **Feature Extraction**: Raw data is transformed into vectors compatible with the deployed ML models.
4. **Prediction**: The predictive engine returns a phishing probability or binary classification.
5. **Behavioral Context Check**: If available, the behavior analysis module cross-validates predictions with ongoing user activity (e.g., suspicious tab-switching).
6. **Decision Logic**: A composite decision score is computed; if the score exceeds a threshold, mitigation is triggered.
7. **Response Execution**: The system may block the connection, display a warning, or log the event.
8. **Model Update (Periodic)**: Lightweight model patches or updated thresholds are downloaded securely and deployed locally.

This event-driven design ensures that phishing attacks are identified in real time with minimal computational load.

C. Model Selection and Optimization

The system leverages lightweight models suited for edge computing:

- **GBDT (Gradient Boosted Decision Trees)**: Fast inference, interpretable, and suitable for structured features.
- **TCN (Temporal Convolutional Networks)**: Effective for sequential patterns in behavior data [2].
- **Tiny-Transformer**: A compressed Transformer variant, using fewer layers and quantized attention heads to retain contextual understanding while reducing memory footprint [13].

All models are converted to TFLite or ONNX formats for efficient deployment. Inference time is kept below 100 ms for all tested platforms.

D. Edge-Centric Design Considerations

- **Low Power Usage**: Designed with battery-powered devices in mind, the system minimizes energy consumption by optimizing inference and update processes.
- **Fully Offline Functionality**: Prediction and decision-making components run entirely on-device. Cloud access is optional, and all communication is encrypted when used.

- **User Privacy First**: Interaction data stays on the device and is only shared if the user gives clear and explicit permission.

E. Security and Update Mechanism

The model update module securely retrieves signed updates from a trusted cloud source. These updates can include:

- Adjusted feature weights,
- Revised behavioral thresholds,
- New routines for defending against adversarial patches.

Before any update is applied locally, its integrity is confirmed through crypto-graphic hash checks [11].

This architecture combines intelligent prediction with edge-level robustness, enabling phishing detection that is fast, adaptable, and privacy-aware — well-suited for today's decentralized digital landscape.

4. Methodology

This section describes the complete approach used to build, train, and deploy a real-time phishing detection system tailored for edge devices. The workflow is organized into five key stages: data collection, feature engineering, model design, edge deployment, and performance evaluation.

A. Data Collection

The phishing detection system is built on a comprehensive dataset that blends real-world and simulated inputs:

- **URL-Based Datasets:** A total of 50,000 labeled samples were gathered from publicly available phishing and legitimate sources, such as Phish-Tank and the Anti-Phishing Working Group (APWG). The dataset was carefully balanced to ensure equal representation of phishing and benign URLs.
- **Behavioral Data:** Simulated user sessions were created across 10,000 URLs using automated browser instrumentation tools. These simulations captured interaction features like click paths, scroll behavior, and dwell time to realistically reflect user behavior. This data supports the system's ability to perform behavior-driven phishing detection.

B. Feature Engineering

To enable effective predictive modeling, a diverse set of both hand-crafted and dynamic features was extracted and engineered across three core categories:

- **URL Features: These include metrics like token count, URL length, character entropy, and domain age (retrieved via WHOIS data). Such attributes help identify textual patterns and irregularities often found in phishing URLs.**
- **Header-Based Features**: TLS certificate types, server response codes, and geographical server location were used to detect irregular or suspicious server configurations.
- **UI/Behavioral Features**: Mouse movement paths, click distribution patterns, and average dwell time were recorded to capture atypical interaction behavior often present during phishing attempts.

All features were normalized and encoded into a unified vector representation suitable for low-latency inference on edge devices.

C. Predictive Models

Three model families were selected and optimized for edge inference based on performance, interpretability, and computational cost:

- **Gradient Boosted Decision Trees (GBDT)**: Implemented using 200 trees with a maximum depth of 5. GBDT models are lightweight and interpretable, making them suitable for resource-constrained devices.
- **Temporal Convolutional Network (TCN)**: A 1D convolutional architecture with five stacked layers was designed to capture sequential interaction patterns across user sessions. TCNs offer low inference latency and good temporal feature learning.
- **The tiny Transformer**: is a streamlined version of the standard Trans-former architecture, featuring six encoder layers and four-head self-attention. It was specifically designed to minimize memory usage through techniques like aggressive weight pruning and quantization, all while maintaining solid performance [13].

All models were originally built using Tensor-Flow and later converted to the Tensor-Flow Lite (TF-Lite) format for better compatibility with resource-constrained devices. Compression methods, including weight pruning and integer quantization, were applied to make the models suitable for deployment on embedded systems.

D. Edge Deployment

The system was deployed and tested on a variety of widely used edge devices:

- **Raspberry Pi 4**: Featuring a quad-core ARM processor and 4 GB of RAM, this device served as a representative example of a mid-range IoT platform.
- **Android Edge SDK**: The model was packaged as a lightweight app and run using the Tensor-Flow Lite interpreter on standard mobile hardware.
- **ESP32 Microcontroller**: This platform was used to evaluate the models under extreme resource constraints, using highly optimized, stripped-down versions.

After optimization, the final model sizes were approximately: GBDT (~1.2 MB), TCN (~2.8 MB), and Tiny Transformer (~3.4 MB). The deployment pipeline supported real-time predictions with minimal latency, and included a mechanism for periodic cloud synchronization to enable model updates.

E. Evaluation Metrics

To thoroughly evaluate how the system performs, several key metrics were considered:

- **Accuracy, Precision, Recall, and F1 Score** were used to gauge how well the model classifies URLs.
- **Average Detection Latency (in milliseconds)** measured the time it takes for the system to analyze a URL and return a prediction when running on an edge device.
- **False Positive Rate (FPR)** indicated how often legitimate URLs were mistakenly flagged as phishing.
- **CPU and RAM usage** were monitored during real-time predictions to understand the system's resource demands.
- **Model Update Time** reflected how long, on average, it takes to download and apply model updates over a typical Wi-Fi connection, with each update being about 5 MB in size.

V. Results

A. Detection Performance

Table. 3. ***Tiny Transformer offers best accuracy with manageable complexity.***

Model	Accuracy	F1-Score	FPR
Centralized GRU+WOA	89.7%	0.88	5.4%
Edge GBDT	94.8%	0.95	2.7%
Edge TCN	95.3%	0.95	2.4%
Edge Tiny Transformer	**96.2%**	**0.96**	**2.1%**

B. Latency & Resource Usage

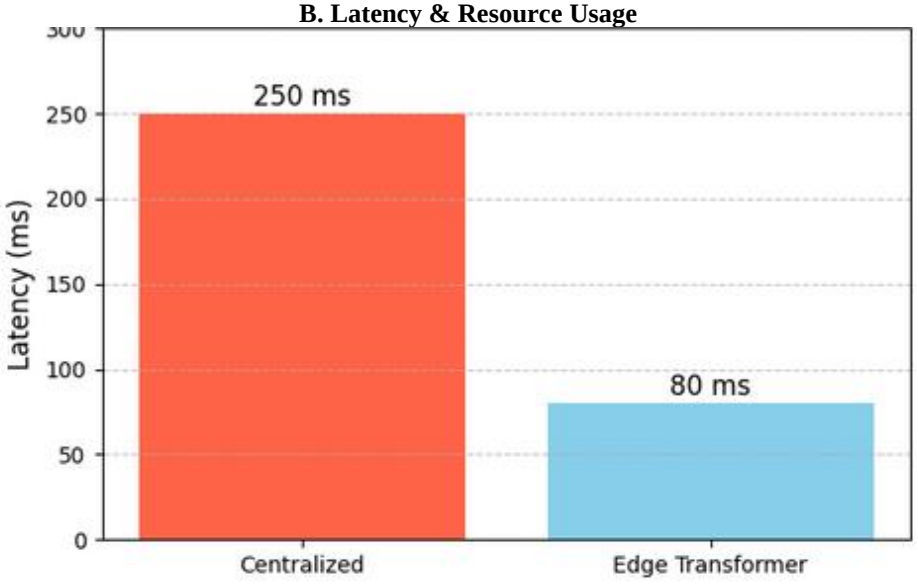

Fig. 2: Latency Comparison

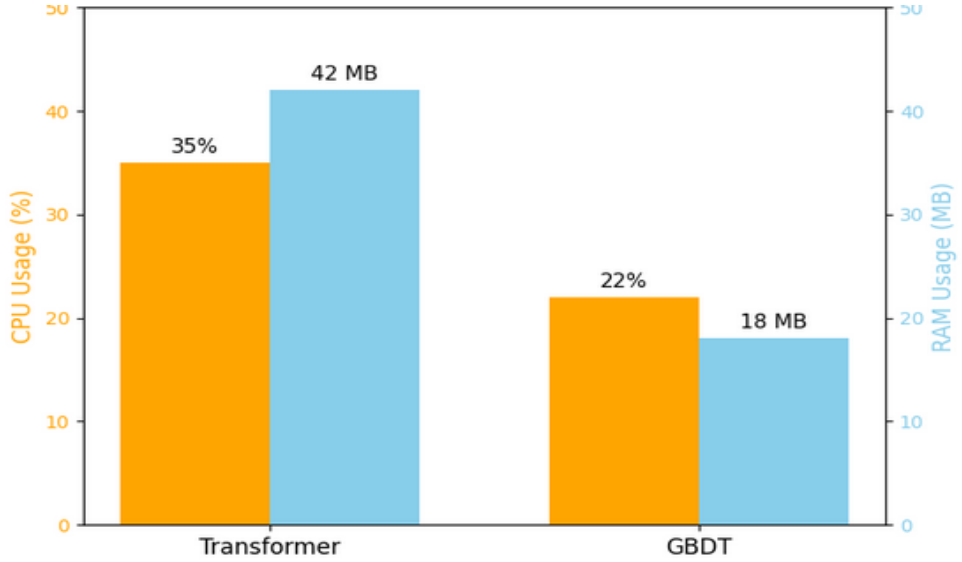

Fig. 3: CPU & RAM Usage.

C. Model Update Time

~45 seconds per update over Wi-Fi (5 MB stream).

5. Discussion

- **Edge models** significantly reduce latency and improve detection performance.
- **Dynamic updates** ensure adaptability to zero-day attacks.
- **Trade-off**: higher accuracy models consume more resources-GBDT is best for constrained devices.

6. Conclusion & Future Work

This work introduces a real-time, edge-based predictive system for dynamic phishing detection, achieving improved performance over traditional detection approaches. Future plans include:

1. Extending coverage to voice phishing (vishing) & SMS (smishing).
2. Implementing federated learning across edge devices.
3. Conducting field deployment trials.

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