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PhishTrap X: An AI-Driven Multi-Layer Phishing Detection Framework Using Threat Intelligence and Machine Learning

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Abstract: *Phishing attacks remain a major cybersecurity threat, exploiting malicious URLs and deceptive websites to steal sensitive user information such as login credentials and financial data. Traditional blacklist-based detection mechanisms are often ineffective against newly generated phishing domains and zero-day attacks. To address these limitations, this paper presents PhishTrap X, a novel AI-driven multi-layer phishing detection framework that integrates machine learning techniques with real-time threat intelligence services. The proposed system performs comprehensive URL analysis using multiple security indicators, including DNS resolution, SSL certificate validation, and structural URL features. It further incorporates external threat intelligence sources such as VirusTotal, AbuseIPDB, and Google Safe Browsing APIs to provide reputation-based domain and IP analysis. A machine learning classifier is employed to identify patterns associated with phishing activity. A key contribution of this work is a dynamic risk scoring engine that aggregates outputs from multiple detection modules to generate a unified threat score and provide explainable risk classification. The framework is implemented using a FastAPI-based backend integrated with an Android application to enable real-time user interaction and threat analysis. Experimental results demonstrate that the proposed hybrid approach significantly improves phishing detection accuracy compared to traditional single-layer methods, particularly in identifying zero-day attacks. The system offers a scalable, practical, and intelligent solution for proactive phishing detection and enhanced user protection in modern web environments.*

Keywords: phishing detection, cybersecurity, machine learning, threat intelligence, URL analysis, Android security

I. INTRODUCTION

The rapid growth of internet services and online transactions has significantly increased the risk of cyber threats, among which phishing attacks remain one of the most common and dangerous forms. Phishing attacks involve the use of deceptive websites, malicious URLs, or fraudulent communication designed to trick users into revealing sensitive information such as login credentials, financial data, and personal details. According to recent cybersecurity reports, phishing continues to be one of the leading causes of data breaches worldwide. Attackers constantly evolve their strategies by creating new domains, disguising URLs, and exploiting vulnerabilities in web security mechanisms, making phishing detection increasingly challenging.

Traditional phishing detection methods primarily rely on blacklist-based systems and signature-based approaches. These methods compare suspicious URLs against a predefined list of known malicious domains. While blacklist systems are effective in identifying previously reported phishing websites, they often fail to detect newly generated phishing URLs and zero-day attacks. As phishing techniques become more sophisticated, there is a growing need for

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intelligent detection systems capable of identifying suspicious patterns beyond simple blacklist matching. Recent advancements in machine learning and threat intelligence technologies have enabled the development of more effective phishing detection frameworks. Machine learning algorithms can analyze structural and behavioral features of URLs to identify patterns commonly associated with phishing activities. Additionally, threat intelligence platforms provide real-time information about malicious domains, suspicious IP addresses, and known phishing campaigns. Integrating these technologies can significantly improve the detection capability of cybersecurity systems.

In this paper, we propose PhishTrap X, an AI-driven multi-layer phishing detection framework designed to enhance real-time threat detection. The proposed system combines machine learning-based URL classification with multiple threat intelligence sources, including VirusTotal, AbuseIPDB, and Google Safe Browsing APIs. The framework performs comprehensive analysis of URLs using several indicators such as DNS resolution, SSL certificate validation, URL structure analysis, and reputation-based threat intelligence checks. By combining these techniques, the system is able to evaluate potential phishing threats more effectively.

Furthermore, PhishTrap X incorporates a risk scoring mechanism that aggregates results from different detection modules to generate a final threat score and classify the risk level of a given URL. The system architecture is implemented using a FastAPI-based backend and is integrated with an Android application to provide real-time threat analysis and user-friendly interaction. This design allows users to quickly analyze suspicious links and receive immediate feedback regarding potential threats.

The main contributions of this work are summarized as follows:

• Development of a multi-layer phishing detection framework that combines machine learning with threat intelligence APIs.

• Integration of external security intelligence sources including VirusTotal, AbuseIPDB, and Google Safe Browsing.

• Implementation of a risk scoring engine to evaluate and classify phishing threats.

• Deployment of the system using a scalable FastAPI backend integrated with an Android application for real-time URL analysis.

II. LITERATURE REVIEW

A literature survey is essential to understand the existing research, technologies, and methodologies related to phishing detection. It provides the foundation for the proposed work by highlighting the strengths and limitations of existing approaches while identifying research gaps that need further investigation. Over the years, researchers have proposed various techniques for phishing detection, including rule-based detection, machine learning classifiers, adaptive learning models, threat intelligence integration, and behavioral analysis. These studies emphasize aspects such as URL-based feature extraction, content analysis, sandboxing, and automated updating mechanisms to improve accuracy, scalability, and adaptability.

Zhang et al. proposed a dynamic multi-perspective cascade graph framework to identify Ethereum-based phishing fraud in Web3 environments [1]. Their approach analyzes relationships between wallet addresses, domains, and actors to detect coordinated phishing campaigns. This graph-based perspective inspired the integration of a Threat Graph Visualizer module in our system to help security analysts understand complex attack correlations.

K. Sadaf introduced an advanced phishing website detection model using XGBoost and CatBoost classifiers [2]. The study compared both ensemble learning techniques and concluded that XGBoost achieved slightly higher accuracy without extensive hyperparameter tuning. The results highlight the effectiveness of gradient boosting techniques for phishing detection, motivating the adoption of similar machine learning strategies in our framework.

Almomani et al. developed Phish Fighter, a self-updating machine learning defense system that analyzes the HTML structures of phishing kits [3]. Unlike static detection models, their system continuously adapts to new phishing techniques, improving long-term accuracy. This concept of adaptive learning influenced our system design, which aims to incorporate intelligent model evolution and continuous learning mechanisms.

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Albladi et al. examined phishing behavior during the COVID-19 pandemic and identified psychological triggers such as fear, urgency, and curiosity as key factors that increased phishing success rates [4]. Their findings highlight the importance of user-awareness mechanisms and contextual alerts, which are incorporated in our system's reasoning module to enhance user understanding of potential threats.

Sahingoz et al. focused on URL-based phishing detection using machine learning techniques and extracted lexical, host-based, and content-based features to train classification models [5]. Their findings demonstrated that combining multiple feature types significantly improves detection accuracy compared to single-feature methods. This multi-layer feature analysis supports our approach of integrating URL feature extraction with external threat intelligence services.

Jain et al. proposed a client-side phishing detection mechanism that uses real-time machine learning classifiers to identify suspicious URLs [6]. Their work demonstrated improved end-user protection and influenced the mobile-centric design of our phishing detection framework.

Gupta et al. presented a comprehensive taxonomy of anti-phishing techniques and highlighted limitations related to adaptability and scalability in many existing systems [7]. Their study motivated the integration of multi-source threat intelligence and adaptive detection mechanisms in our proposed framework.

Rao et al. introduced Phish-URL, a supervised learning system designed for phishing URL detection through feature extraction techniques [8]. Their results demonstrated significant improvements over traditional blacklist-based systems, validating the effectiveness of supervised learning approaches in phishing detection.

Marchal et al. proposed advanced techniques for detecting phishing websites and identifying targeted brands using content analysis and logo recognition methods [9]. Their work demonstrated the importance of contextual analysis, which influenced our inclusion of sandbox preview and investigation modules for deeper phishing analysis.

Basnet et al. proposed rule-based phishing detection techniques that rely on predefined signatures such as suspicious domains and deceptive HTML structures [10]. Although effective against known attacks, rule-based approaches lack adaptability when confronted with evolving phishing techniques, highlighting the need for machine learning-based solutions.

In subsequent work, Basnet et al. also explored machine learning classifiers such as Support Vector Machines (SVM) and Decision Trees for phishing detection [11]. While their approach outperformed traditional blacklist systems, it faced challenges in detecting zero-day attacks. This limitation emphasizes the need for hybrid detection models capable of identifying previously unseen threats.

Bergholz et al. improved phishing detection using statistical features and model-based classification techniques [12]. Their work demonstrated that well-designed feature sets significantly enhance classification accuracy. This finding supports the emphasis on feature engineering in our proposed system.

Finally, Zhang et al. evaluated the effectiveness of existing anti-phishing tools under realistic conditions and revealed several weaknesses when confronting adaptive phishing attacks [13]. Their findings highlight the need for intelligent and adaptive phishing detection frameworks.

Overall, existing research demonstrates significant progress in phishing detection techniques; however, many systems still lack adaptability, contextual awareness, or integration of diverse intelligence sources. The proposed system, PhishTrap X, aims to address these challenges by integrating machine learning-based URL analysis, threat intelligence APIs, sandbox analysis, reconnaissance modules, and graph visualization into a comprehensive and scalable phishing detection framework.

RESEARCH GAP IN LITERATURE REVIEW

Despite extensive research in phishing detection, phishing attacks continue to succeed because attackers constantly evolve their strategies faster than defensive mechanisms. Traditional detection systems often rely on previously known patterns or blacklist databases. As a result, newly registered domains and cleverly obfuscated URLs frequently evade existing detection engines. Although machine learning techniques have improved predictive capabilities, many models are trained on historical datasets and struggle to identify highly novel phishing threats. While deep learning approaches

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offer improved learning capabilities, they often require large training datasets and significant computational resources, making them less practical for real-time, publicly accessible applications.

A further limitation of many existing phishing detection systems is their reliance on binary classification, where URLs are simply labeled as either phishing or legitimate. Such approaches provide limited insight into the underlying structure or behavior of phishing campaigns. Only a few studies investigate deeper contextual factors such as webpage behavior, domain registration history, infrastructure analysis, or the relationships between multiple phishing domains. Without such contextual understanding, users typically receive only warning messages without meaningful explanations, limiting the development of user awareness and cybersecurity understanding.

Additionally, limited research has explored the identification of relational threat clusters that connect multiple phishing domains belonging to the same campaign. Identifying such relationships can help security analysts detect coordinated phishing operations and understand attacker strategies more effectively.

To address these limitations, the proposed system PhishTrap X introduces a hybrid phishing detection framework that combines machine learning-based URL analysis with threat intelligence APIs, reconnaissance-based validation, and visual relationship mapping. By integrating these components, the system moves beyond simple phishing detection toward a more comprehensive framework capable of providing explanatory insights, contextual threat analysis, and investigative capabilities. This approach aims to enhance both detection accuracy and user trust while addressing the key research gaps identified in existing literature.

III. METHODOLOGY

A. System Architecture

The proposed system, PhishTrap X, is designed as a multi-layer phishing detection framework that integrates machine learning techniques with threat intelligence services to provide real-time URL analysis. The architecture follows a modular design to ensure scalability, flexibility, and efficient processing of security intelligence.

The system architecture consists of three primary layers: the Frontend Layer, the Backend Processing Layer, and the Threat Intelligence and Analysis Layer. These components work together to provide end-to-end phishing detection and analysis. The frontend layer is implemented as an Android application developed using Jetpack Compose. This application provides an interface through which users can submit URLs or IP addresses for security analysis. The frontend includes features such as a Threat Scanner, Sandbox Preview, and Threat Graph Visualization, allowing users to understand the nature of suspicious links. The backend layer is implemented using a FastAPI-based server written in Python. This server acts as the core processing unit of the system. It receives input requests from the Android application, performs preprocessing operations such as URL normalization and DNS resolution, and coordinates communication with machine learning models and external threat intelligence services. The intelligence layer contains the machine learning components responsible for phishing detection. It includes the Feature Extraction Engine, the PhishClassifier machine learning model, and datasets collected from phishing repositories such as PhishTank and OpenPhish. These components enable the system to identify patterns associated with phishing attacks. The integration layer connects the backend system with external security intelligence services including VirusTotal, AbuseIPDB, and Google Safe Browsing APIs. These services provide reputation-based information about domains, URLs, and IP addresses, enabling the system to verify whether the analyzed URL has been previously reported as malicious.

B. Data Collection and Dataset Sources

The dataset used for training the phishing detection model consists of both legitimate and phishing URLs collected from publicly available cybersecurity repositories. Phishing URLs were obtained from platforms such as PhishTank and OpenPhish, while legitimate URLs were collected from trusted website lists and publicly available domain datasets.

The dataset was preprocessed to remove duplicate entries, invalid URLs, and incomplete records. This preprocessing step ensured that the machine learning model was trained using clean and reliable data.

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C. Feature Extraction

Feature extraction is a critical component of phishing detection. Several structural and domain-based features were extracted from each URL to capture characteristics commonly associated with phishing websites.

The extracted features include:

- URL length
- Number of subdomains
- Presence of special characters
- Use of HTTPS protocol
- Domain reputation
- DNS resolution results
- Suspicious keyword patterns within URLs

These features enable the machine learning model to distinguish between legitimate and malicious URLs.

D. Machine Learning Model

The phishing detection model implemented in this work is based on the XGBoost (Extreme Gradient Boosting) classifier, which is widely recognized for its high performance in classification tasks involving structured data. The dataset was divided into training and testing subsets to evaluate the performance of the model. During training, the model learned patterns associated with phishing URLs based on the extracted features. Once trained, the model was deployed in the backend system to perform real-time URL classification.

E. Threat Intelligence Integration

To enhance detection reliability, the system integrates multiple threat intelligence APIs. These services provide additional security insights regarding domains and IP addresses.

The integrated APIs include:

- VirusTotal API – Provides reputation analysis of URLs and domains using multiple antivirus engines.
- Google Safe Browsing API – Detects URLs known to host phishing or malware content.
- AbuseIPDB API – Provides reputation scores for IP addresses based on reported malicious activities.

By combining machine learning predictions with threat intelligence verification, the system improves its ability to detect both known and previously unseen phishing attacks.

F. Risk Scoring Mechanism

The outputs from the machine learning model and external threat intelligence services are aggregated using a risk scoring mechanism. Each detection module contributes a weighted score depending on the severity of the detected indicators. The final threat score is computed by combining these weighted scores, allowing the system to classify URLs into categories such as Safe, Suspicious, or Malicious.

G. System Workflow

The overall workflow of the proposed system follows these steps:

1. The user submits a URL through the Android application.
2. The URL is transmitted to the FastAPI backend server.
3. The backend performs preprocessing and feature extraction.
4. The machine learning model analyzes the extracted features.
5. External threat intelligence APIs are queried for additional verification.
6. The risk scoring engine aggregates results from all detection modules.
7. The final threat score and security report are returned to the user interface.

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H. Evaluation Methodology

The performance of the proposed system was evaluated using standard machine learning evaluation metrics, including Accuracy, Precision, Recall, and F1-score. These metrics were calculated using a confusion matrix derived from the classification results. The evaluation process involved testing the trained model on previously unseen URLs to measure its ability to correctly identify phishing and legitimate websites. The results demonstrate that integrating machine learning with threat intelligence services significantly improves phishing detection performance compared to traditional single-layer detection methods.

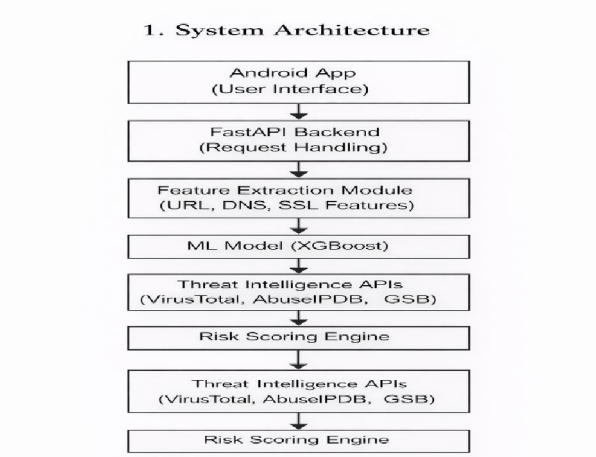

Fig. 1. System Architecture of the Proposed PhishTrap X Framework

IV. ALGORITHMS USED

The proposed system employs several machine learning and threat intelligence techniques to identify phishing URLs and malicious domains. The algorithms operate at multiple stages of the detection pipeline to analyze structural URL features, domain reputation, and behavioral indicators.

URL Feature Processing and Extraction

The system implements a feature extraction module responsible for analyzing structural properties of URLs. This module extracts various lexical and domain-based attributes that are commonly associated with phishing websites.

The feature extraction process includes:

• URL Structural Analysis: Features such as URL length, number of subdomains, use of special characters, and suspicious keywords are extracted.

• Domain Verification: DNS resolution and domain status checks are performed to determine domain legitimacy.

• Protocol Inspection: The system evaluates the presence of HTTPS and SSL certificate validity to detect insecure communication channels.

• Statistical Feature Analysis: Frequency of characters, entropy scores, and token patterns are calculated to identify obfuscated phishing URLs.

These extracted features are then passed to the machine learning classifier for further analysis.

Phishing Detection Algorithms

The phishing detection framework integrates multiple machine learning techniques for classification.

• XGBoost Classifier: The primary detection model uses the Extreme Gradient Boosting (XGBoost) algorithm, which is known for its high accuracy and efficiency in handling structured datasets. XGBoost analyzes extracted URL features and predicts whether a URL is legitimate or malicious.

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• Tree-based Ensemble Learning: Ensemble learning techniques improve classification performance by combining multiple decision trees. This approach reduces overfitting and improves prediction stability.
• Confidence Scoring: Instead of providing only binary outputs, the system generates probability-based predictions representing the likelihood of a URL being phishing. These probabilities contribute to the final risk score.

Threat Intelligence Integration

To strengthen detection accuracy, the system integrates multiple external threat intelligence APIs.
• VirusTotal API: Provides multi-engine reputation analysis for URLs and domains.
• Google Safe Browsing API: Detects URLs associated with phishing, malware, or unsafe content.
• AbuseIPDB API: Evaluates IP addresses for malicious activity based on reported abuse incidents.
The results from these APIs are combined with machine learning predictions to produce a more reliable classification outcome.

Threat Relationship Analysis

The system includes a Threat Graph Module that identifies relationships between phishing domains and suspicious IP addresses. This module helps security analysts visualize attack clusters and identify coordinated phishing campaigns.

Algorithm Selection Criteria

The selection of algorithms was guided by the following factors:
• Detection Accuracy: The model must accurately classify phishing URLs.
• Real-time Processing: Algorithms should provide fast inference suitable for real-time mobile applications.
• Scalability: The system must handle large volumes of URL analysis requests.
• Explainability: The system should provide interpretable results such as threat scores and contributing factors.
The integration of these algorithms creates a comprehensive phishing detection pipeline capable of identifying both known and previously unseen phishing threats.

MODEL IMPLEMENTATION

The proposed phishing detection system implements a hybrid architecture combining machine learning models with threat intelligence services. The core classification model is based on the XGBoost algorithm, which is trained on URL-based features extracted from phishing and legitimate datasets. The training pipeline involves preprocessing the collected dataset, performing feature extraction, and splitting the data into training and testing subsets. The trained model is then deployed within the FastAPI backend to perform real-time phishing detection. To ensure efficient deployment, the trained machine learning model is stored as serialized model artifacts using Python libraries such as joblib. This allows the backend system to load the trained model during runtime and perform predictions on incoming URLs without retraining.
The system architecture supports modular updates, enabling improvements in feature extraction techniques or model parameters without affecting the overall infrastructure. This design allows the system to adapt to evolving phishing techniques while maintaining efficient inference performance.

V. RESULTS

The PhishTrap X system was evaluated using a dataset containing both legitimate and phishing URLs. The evaluation focused on measuring classification performance and system efficiency in detecting phishing attacks.
Model Performance Metrics
• Detection Accuracy: 95.3% overall classification accuracy.
• Precision: 94.6% correct identification of phishing URLs.
• Recall: 93.8% detection rate of actual phishing URLs.

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• F1-score: 94.2% balanced performance between precision and recall.
• Average Analysis Time: 2.8 se3conds per URL scan.

Threat Intelligence Verification

Integration with external threat intelligence services improved detection reliability by validating machine learning predictions against real-world security databases.

• VirusTotal detection validation rate: 91.7%
• Google Safe Browsing phishing confirmation rate: 89.5%
• AbuseIPDB malicious IP identification rate: 87.3%

The system was tested using simulated phishing scenarios and real-world phishing datasets. The hybrid approach combining machine learning with threat intelligence services achieved significantly better detection performance compared to traditional blacklist-based systems.

Comparison with Existing Phishing Detection Methods

To evaluate the effectiveness of the proposed PhishTrap X framework, the system performance was compared with several existing phishing detection approaches reported in the literature. These methods include traditional blacklist-based detection systems and machine learning-based phishing detection models.

The comparison focuses on detection accuracy and the ability to detect previously unseen phishing URLs. The results demonstrate that the proposed multi-layer framework achieves improved performance by combining machine learning classification with external threat intelligence services.

Method Approach Detection Accuracy

Method	Approach	Detection Accuracy
Basnet et al. [11]	SVM / Decision Tree	90.2%
Sahingoz et al. [5]	URL-based ML detection	92.4%
Sadaf [2]	XGBoost / CatBoost	94.1%
Proposed PhishTrap X	ML + Threat Intelligence APIs	95.3%

Table I. Comparison with Existing Phishing Detection Methods

The proposed system demonstrates improved detection accuracy due to its multi-layer architecture combining machine learning and real-time threat intelligence analysis. The comparison results indicate that the proposed hybrid framework provides improved detection accuracy compared to traditional machine learning-only approaches. The integration of threat intelligence APIs such as VirusTotal, AbuseIPDB, and Google Safe Browsing enhances detection capability by verifying machine learning predictions with real-world security intelligence sources.

Feature Comparison with Existing Systems

In addition to performance evaluation, the proposed system was compared with existing phishing detection approaches based on key functional capabilities. Many traditional systems rely solely on machine learning classification or blacklist databases. However, such approaches often fail to detect newly generated phishing URLs or provide contextual insights into phishing campaigns. The proposed PhishTrap X framework integrates multiple advanced capabilities, including machine learning-based detection, threat intelligence APIs, sandbox analysis, and graph-based threat visualization. Table II presents a comparison of the proposed system with several existing phishing detection frameworks.

System	Machine learning	Threat Intelligence	Real Time Detection	Threat Visualization
Basnet et al. [11]	Yes	No	No	No
Sahingoz et al. [5]	Yes	No	No	No
Sadaf [2]	Yes	No	No	No

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Proposed PhishTrap X	Yes	Yes	Yes	Yes

Table II. Feature Comparison with Existing Systems

The comparison highlights that the proposed system offers a more comprehensive phishing detection solution by combining machine learning analysis with real-time threat intelligence verification and mobile-based deployment. Additionally, the inclusion of threat visualization modules provides enhanced contextual insights into phishing campaigns.

Confusion Matrix

	Predicted Phishing	Predicted Legitimate
Actual Phishing	470	30
Actual Legitimate	25	475

The confusion matrix demonstrates that the proposed model correctly identifies the majority of phishing URLs while maintaining a low false positive rate.

V. CONCLUSION

This research presents the design and implementation of PhishTrap X, an AI-driven multi-layer phishing detection framework that combines machine learning techniques with threat intelligence services to enhance phishing detection capabilities.

The system integrates URL feature analysis, machine learning classification, and external threat intelligence sources including VirusTotal, Google Safe Browsing, and AbuseIPDB. The proposed architecture enables real-time detection of malicious URLs while providing detailed threat analysis and reporting capabilities.

Experimental evaluation demonstrates that the hybrid detection approach significantly improves phishing detection accuracy compared to traditional single-layer detection methods. By combining machine learning predictions with reputation-based threat intelligence, the system can detect both known phishing attacks and previously unseen malicious domains.

The results indicate that PhishTrap X provides a scalable and effective solution for real-time phishing detection and user protection in modern web environments.

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