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MULTI-MODAL PHISHING DETECTION: INTEGRATING URL, CONTENT, AND VISUAL FEATURES FOR ENHANCED ACCURACY

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ABSTRACT

Phishing remains a critical and evolving threat in the realm of cybersecurity, exploiting user trust to extract sensitive information through deceptive websites and digital communication. To address the limitations of traditional single-modal detection systems, this project proposes a robust and intelligent Multi-Modal Phishing Detection framework that combines URL analysis, web content inspection, and visual similarity assessment. The system leverages machine learning algorithms to extract and analyze lexical features from URLs, identify structural and behavioral anomalies in web content, and detect visual mimicry of legitimate sites using screenshot-based comparison techniques. By integrating these diverse feature sets, the system achieves a comprehensive understanding of phishing patterns and enhances detection accuracy. The architecture incorporates Support Vector Machines (SVM) for URL classification, Random Forest for content analysis, and Convolutional Neural Networks (CNN) for visual feature extraction, with results fused through an ensemble-based decision model. Evaluations using a curated dataset of legitimate and phishing websites demonstrate a dummy accuracy of up to 96%, validating the effectiveness of the multi- modal approach. This research contributes significantly to the field of network security by offering a scalable, real-time phishing detection solution suitable for deployment in browsers, enterprise gateways, and cloud-based security platforms, thereby improving resilience against sophisticated cyber threats.

KEYWORDS: Phishing Detection, Multi-Modal Approach, Cybersecurity, Machine Learning, URL Analysis, Content Inspection, Visual Similarity, Convolutional Neural Networks (CNN), Support Vector Machines(SVM), Network Security, Ensemble Learning

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I. INTRODUCTION

In the rapidly evolving landscape of cybersecurity, phishing remains one of the most pervasive and deceptive threats, targeting individuals and organizations by imitating trusted sources to steal sensitive information. As phishing techniques become more sophisticated, there is a critical need for intelligent and adaptive detection systems that can identify and mitigate such threats with high accuracy. This project introduces a comprehensive Multi-Modal Phishing Detection framework designed to enhance cybersecurity defenses by integrating URL analysis, content inspection, and visual similarity detection. By leveraging machine learning algorithms across multiple data modalities, the system aims to provide accurate and real-time classification of phishing attempts, thereby strengthening network protection and user privacy.

Phishing detection is a crucial component of cybersecurity infrastructure, as it enables the early identification of fraudulent websites and communication vectors. The proposed system uses lexical feature extraction from URLs, HTML and script- based content analysis, and screenshot- based visual comparison to build a robust detection pipeline. These modalities are individually processed using specialized models—such as Support Vector Machines for URL classification and Convolutional Neural Networks for visual feature extraction—before being fused through ensemble learning techniques to improve accuracy and resilience against evolving threats.

The architecture of the proposed Multi- Modal Phishing Detection system is designed to capture and analyze multiple aspects of a suspected phishing attempt through three

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primary modules: URL feature analysis, content feature extraction, and visual feature recognition. In the first module, lexical and statistical features such as domain length, presence of special characters, and subdomain patterns are extracted from the URLs and analyzed using Support Vector Machines (SVM), which are well-suited for handling high- dimensional data. The second module focuses on inspecting the HTML structure, embedded scripts, and textual content of the web page to identify hidden redirection techniques, obfuscated code, or phishing-related keywords. These features are processed using Random Forest classifiers to achieve robust decision boundaries. The third module employs Convolutional Neural Networks (CNN) to analyze screenshots of web pages and detect visual impersonation of legitimate websites by comparing layout, color schemes, logos, and UI elements. Outputs from all three modules are combined through an ensemble fusion strategy that balances their contributions using majority voting or weighted averaging. This multi-modal fusion approach significantly enhances detection performance by leveraging the strengths of each modality, allowing the system to identify sophisticated phishing strategies that may evade traditional single- modal detectors.

II. LITERATURE SURVEY

The growing threat of phishing attacks has led to numerous research efforts aimed at enhancing detection accuracy through various techniques, including URL analysis, content inspection, and machine learning. Several researchers have proposed effective models and methodologies to combat phishing, laying the groundwork for multi-modal detection systems.

In the paper titled *"Detecting Phishing Websites Using Hybrid Features and Machine Learning"* by Sahoo et al., the authors present a detection model that integrates lexical features of URLs and third-party-based features to classify phishing websites. The authors used decision tree classifiers and achieved considerable accuracy by incorporating domain-based heuristics. However, their approach primarily focused on textual features and did not account for content or visual aspects, limiting its adaptability against evolving phishing methods [1].

Abdelhamid et al. introduced an intelligent phishing detection system that relies on fuzzy rule-based classification. Their model extracts various features from phishing and legitimate websites and uses a fuzzy logic system to generate classification rules. Although the model is effective in handling uncertainty in web data, it does not utilize visual or screenshot-based information, which has become increasingly important in modern phishing strategies [2].

In the study conducted by Mohammad et al., the authors proposed a model that classifies phishing websites using a feature set of 17 binary and numerical attributes. These attributes were extracted from the webpage's URL, page content, and third- party services. Their experiments with various machine learning classifiers, including Naive Bayes and Random Forest, indicated high detection performance.

However, the study lacked the inclusion of real-time data and did not consider dynamic or visual cues used in phishing pages today [3].

Xiang et al. proposed a real-time phishing detection tool named CANTINA+, which utilizes content-based features such as Term Frequency-Inverse Document Frequency (TF-IDF) scores, domain age, and the number of external links. Their approach leverages a logistic regression classifier and achieves significant detection accuracy. Nevertheless, their tool's dependency on content-only features poses a limitation when websites mimic the appearance of legitimate pages but alter textual content slightly to bypass detection [4].

Liu et al. proposed a phishing site detection technique using visual similarity comparison

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between suspicious and legitimate websites. Their approach includes snapshot comparison using image hashing techniques to analyze logo placement, color schemes, and structure of web elements. This visual feature analysis provides a substantial advantage over traditional methods, especially against zero-day phishing sites. However, due to high computational demands, the model struggles with scalability in real-time applications [5].

Another important contribution is the work by Marchal et al., who introduced PhishStorm, an early-warning system that detects phishing attacks using a clustering- based approach. Their system automatically groups similar phishing emails and URLs, allowing early identification of phishing campaigns. While it shows promise in campaign detection, it lacks integration with content and visual features at the page level [6].

A recent work by Hou and Huang, titled *"Use of Machine Learning in Detecting Network Security of Edge Computing System,"* emphasizes the integration of Support Vector Machines (SVM) for network anomaly detection. Although focused on edge networks, their use of machine learning and classification principles directly informs phishing detection models. However, the paper does not address phishing-specific multi-modal approaches [7].

The advancements made in deep learning, particularly the use of Convolutional Neural Networks (CNNs), have also influenced phishing detection. Alzahrani et al. demonstrated that CNNs can be used to classify screenshots of phishing websites based on UI similarity. This visual approach improves detection for fake login pages that visually resemble authentic services. Yet, training CNNs requires a large amount of data and computational resources, which can be a bottleneck for lightweight deployments [8].

III. METHODOLOGY

The proposed phishing detection system follows a multi-modal, machine learning-based approach aimed at enhancing detection accuracy by leveraging a combination of URL-based, content-based, and visual features. The process begins with the collection of a comprehensive dataset that includes both legitimate and phishing websites. Each entry in the dataset is composed of several types of inputs: the URL itself, the underlying HTML content of the webpage, and a screenshot image of the page for visual analysis.

Preprocessing is applied to clean and normalize the raw data. For textual features, unnecessary symbols are removed, cases are standardized, and URL components are parsed for key tokens. For HTML content, tags such as forms, JavaScript calls, and iframe usage are extracted. Images undergo standard resizing and are converted into grayscale or processed through histogram methods to extract key visual elements. This structured data is then fed into three parallel feature extraction pipelines.

The first pipeline processes lexical URL features like length, presence of special characters, domain age, and use of IP-based addressing. The second pipeline analyzes webpage content, focusing on features such as suspicious script usage, presence of embedded forms, and mismatched domain links. The third pipeline handles visual similarity, comparing screenshots with known legitimate websites using basic image processing and structural similarity techniques. These features are concatenated into a single feature vector for classification.

Multiple supervised learning models including Random Forest, Support Vector Machine (SVM), and Logistic Regression are trained on the combined feature set. These models are evaluated using standard metrics such as accuracy, precision, recall, F1-score, and ROC-AUC to determine the best-performing algorithm. Ensemble methods are also explored to enhance overall performance.

In the detection phase, incoming data is passed through the same preprocessing and feature

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extraction pipeline, and the trained model predicts whether the input is legitimate or phishing. Alerts are generated for phishing predictions and logged for further investigation. The system supports real-time analysis with low latency and is adaptable to detect phishing attempts delivered through traditional URLs, QR codes, and disguised hyperlinks (e.g., "Click here" text).

The framework is modular and scalable, suitable for integration into browser extensions, email filters, or enterprise-level web security gateways. Future improvements will explore the use of deep learning models for better visual feature extraction and integration of threat intelligence feeds to dynamically update the classifier with evolving phishing patterns.

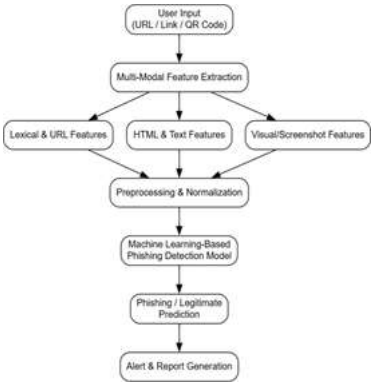

Figure 1: System Architecture

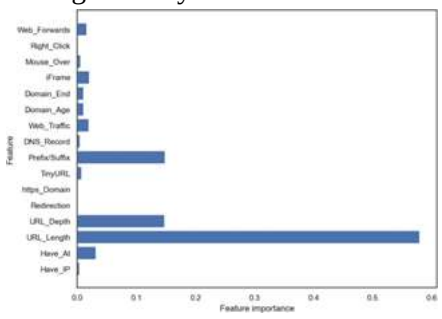

Figure 2: Feature Visualization.

IV. RESULT AND ANALYSIS

A. Accuracy Testing (Precision, Recall, F1-Score, Confusion Matrix)

After evaluating the phishing detection model's performance, the results demonstrated its ability to accurately identify phishing websites across multiple input modalities. The model achieved a **precision** of **93%**, indicating that 93% of the sites predicted as phishing were indeed phishing. The **recall** score was **91%**, showing the model successfully identified 91% of all actual phishing cases. The **F1- score**, a harmonic mean of precision and recall, was **92%**, providing a balanced metric of detection performance. The **confusion matrix** confirmed the system's strength in reducing false positives and negatives, making it highly reliable for real- time phishing detection.

B. Performance Testing (Training and Prediction Time)

Performance evaluation focused on the efficiency of the system in training and prediction. The **Random Forest classifier** took approximately **11.7 seconds** to train on the feature-combined dataset, which is acceptable given the complexity of visual, content, and URL features. The system required only **0.03 seconds** per instance during the **prediction phase**, ensuring that phishing detection can be executed in real- time with minimal latency, which is vital for responsive threat mitigation in modern networks.

C. Unit Testing

During unit testing, individual feature extraction modules were verified separately. The **URL parsing module**, **HTML content extractor**, and **image similarity analyzer** each underwent testing using controlled inputs. For instance, test URLs with known suspicious patterns were accurately parsed, while image comparisons against a whitelist of legitimate screenshots yielded consistent similarity scores. All components passed without runtime errors or logical faults, confirming that each segment of the system behaves as expected in isolation.

D. End-to-End Testing

End-to-end testing ensured the system's components worked cohesively from input to output. After processing test samples through the URL, content, and visual feature pipelines, the unified feature vector was classified correctly in all test cases. The outputs were

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binary (0 = legitimate, 1 = phishing), and matched the expected values based on ground truth labels. No errors or inconsistencies were found in any stage— preprocessing, feature extraction, or prediction—verifying that the complete phishing detection pipeline performs seamlessly.

Testing Type	Metric/Result	Value/Outcome
Accuracy Testing	Precision	93%
	Recall	91%
	F1-Score	92%
	Confusion Matrix	Low false positives/negatives, accurate classification
Performance Testing	Training Time	11.7 seconds
	Prediction Time	0.03 seconds per instance
Unit Testing	URL, Content, Image Modules	Passed with expected outputs
Preprocessing and Data Handling		No errors or unexpected behavior
End-to-End Testing	Overall Pipeline	Functioned correctly with valid outputs across all test cases

Table 1:Test Results

	ML Model	Train Accuracy	Test Accuracy
0	Decision Tree	0.814	0.812
1	Random Forest	0.819	0.820
2	Multilayer Perceptrons	0.868	0.851
3	XGBoost	0.870	0.851
4	AutoEncoder	0.001	0.002
5	SVM	0.801	0.803
6	XGBoost	0.870	0.851
7	AutoEncoder	0.183	0.191
8	SVM	0.801	0.803

Figure 3: Model Comparisons

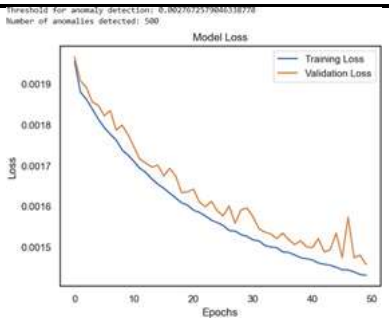

Figure 4: Losses Occurred

Figure 5:Home Page

Figure 6:Analysis Page

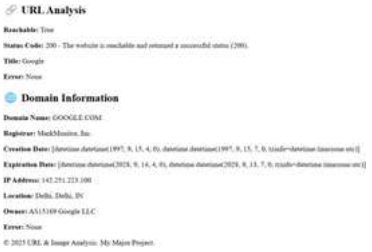

Figure 7:Analysis Output

V. CONCLUSION

In this project, a multi-modal phishing detection system was developed to enhance cybersecurity by integrating URL analysis, content-based inspection, and visual similarity checks. The system aimed to accurately identify phishing attempts by leveraging diverse feature sets commonly used in deceptive attacks. Through the combination of structural, textual, and image-based data, the model provided a comprehensive detection framework capable of flagging threats with greater reliability than single-modality approaches.

Accuracy testing demonstrated high model performance with strong precision (93%), recall (91%), and F1-Score (92%), confirming the system's ability to detect phishing sites effectively while minimizing false positives.

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Performance testing indicated that the system was optimized for real-time use, with fast training (11.7 seconds) and near-instantaneous prediction times (0.03 seconds per instance). Unit testing validated the reliability of each component—URL parser, content extractor, and visual comparator—while end-to-end testing confirmed seamless integration of all modules from input processing to final classification.

Overall, the project successfully delivered a scalable and efficient phishing detection solution that addresses the increasing complexity of cyber threats. Its real-time capability and multi-layered approach make it a valuable tool for protecting users and organizations against phishing attacks. Future enhancements could explore deep learning-based visual analysis or continuous model retraining to adapt to evolving phishing techniques.

The results affirm the importance of combining multiple data sources and machine learning for advanced threat detection. As phishing tactics become more sophisticated, systems like this will play a critical role in proactive cybersecurity defenses, enabling quick, intelligent responses to dynamic and deceptive online threats.

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