# Explainable Multi-Modal Phishing Detection Using Lightweight Deep Learning

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***Abstract*—Phishing attacks continue to pose a serious threat to online security by exploiting both deceptive URLs and manipulated webpage content. Many existing detection approaches rely on single-source features or complex models that lack transparency and are difficult to deploy in real-time environments. To address these challenges, this paper presents a lightweight and explainable multi-modal framework for phishing detection. The proposed system combines structural URL characteristics with relevant webpage content features to capture a more complete representation of phishing behaviour. A computationally efficient deep learning model is utilized to ensure faster prediction with reduced resource consumption. In addition, a feature selection process is applied to eliminate redundant information and enhance model performance. To improve trust and interpretability, an explainable AI mechanism is incorporated to highlight the key factors influencing classification decisions. The experimental evaluation demonstrates that the proposed approach achieves better accuracy and lower false positive rates compared to conventional techniques. The system is designed for practical deployment and can be effectively used in real-time cybersecurity applications such as browser-based protection tools.**

***Index Terms*—Phishing Detection, Multi-Modal Learning, Explainable AI, Lightweight Deep Learning, URL Analysis, Cybersecurity**

## I. INTRODUCTION

The rapid growth of internet-based services and digital transactions has significantly increased the risk of cybersecurity threats, among which phishing attacks remain one of the most prevalent and harmful. Phishing is a fraudulent technique in which attackers create deceptive websites or URLs that closely resemble legitimate platforms in order to trick users into revealing sensitive information such as login credentials, banking details, and personal data. As phishing strategies continue to evolve in complexity, traditional detection methods are becoming less effective in identifying these malicious activities.

Conventional phishing detection approaches, such as blacklist-based and rule-based systems, rely on previously known attack patterns and manually defined rules. Although these methods are simple and computationally efficient, they fail to detect newly generated or zero-day phishing URLs and require frequent updates. To overcome these limitations, machine learning and deep learning techniques have been widely adopted, enabling automated detection by learning patterns from data. However, many existing models rely only on URL-based features or operate as black-box systems, which limits their adaptability and reduces interpretability.

In recent years, there has been growing interest in developing multi-modal phishing detection systems that combine multiple data sources, such as URL features and webpage content, to improve detection accuracy. At the same time, the need for model transparency has led to the integration of Explainable Artificial Intelligence (XAI) techniques, which provide insights into the decision-making process of complex models. Despite these advancements, challenges such as high computational cost, lack of real-time performance, and limited adaptability to evolving phishing techniques still persist.

To address these challenges, this paper proposes an explainable multi-modal phishing detection framework that integrates structural URL analysis with webpage

content features using a lightweight deep learning model. The proposed system is designed to achieve high accuracy while maintaining computational efficiency, making it suitable for real-time applications. Additionally, the incorporation of an explainable AI module enhances transparency by providing clear explanations for model predictions. The system also includes an adaptive learning mechanism to improve its ability to detect emerging phishing patterns.

Overall, the proposed approach aims to provide a scalable, efficient, and interpretable solution for phishing detection, contributing to improved cybersecurity in modern web environments.

## II. PROBLEM STATEMENT

Phishing attacks continue to grow in frequency and sophistication, posing a significant threat to online security and user privacy. Attackers increasingly exploit both deceptive URL structures and manipulated webpage content to create highly convincing phishing websites. Traditional detection methods, such as blacklist-based and rule-based approaches, are limited in their ability to identify newly generated and zero-day phishing URLs, as they rely heavily on previously known patterns and require continuous manual updates. Although machine learning and deep learning techniques have improved phishing detection performance, many existing models depend solely on URL-based features or operate as complex black-box systems. This results in limited adaptability to evolving phishing strategies, increased computational complexity, and lack of interpretability, making it difficult for users to understand the reasoning behind predictions. Furthermore, single-modal approaches often fail to capture the complete characteristics of phishing attacks, leading to reduced accuracy and higher false positive rates.

Therefore, there is a need for an efficient and robust phishing detection system that can integrate multiple data sources, provide interpretable results, and operate effectively in real-time environments. The system should be capable of detecting both known and emerging phishing attacks while maintaining high accuracy, low computational overhead, and improved user trust.

## III. LITERATURE SURVEY

Phishing detection has become a critical area of research due to the rapid growth of online services and the increasing sophistication of cyberattacks. Phishing websites exploit deceptive URLs and manipulated webpage content to mislead users into disclosing sensitive information such as login credentials and financial details. Traditional detection techniques are often insufficient in identifying advanced and zero-day phishing attacks, leading researchers to explore machine learning, deep learning, and hybrid approaches. However, many existing methods still face challenges related to accuracy, adaptability, computational cost, and lack of interpretability.

### A. Traditional Phishing Detection Approaches

Initial phishing detection systems primarily relied on blacklist-based and rule-based methods. Blacklist techniques compare URLs against a stored list of known phishing websites, while rule-based systems use predefined heuristics such as URL length, presence of special characters, and suspicious keywords. Although these approaches are simple and computationally efficient, they fail to detect newly generated phishing URLs and require frequent updates. As a result, they are ineffective against dynamic and evolving phishing attacks.

### B. Machine Learning-Based Detection

To improve detection performance, machine learning techniques have been widely adopted. Algorithms such as Support Vector Machines (SVM), Decision Trees, Naïve Bayes, and Random Forest utilize handcrafted features derived from URL structure and domain characteristics. These methods have shown better accuracy compared to traditional approaches. However, their effectiveness depends heavily on feature engineering, and they often struggle to generalize well to unseen phishing patterns, especially in rapidly changing environments.

### C. Deep Learning-Based Approaches

Deep learning techniques have gained popularity due to their ability to automatically extract features from raw data. Models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), including Long Short-Term Memory (LSTM), are commonly used to analyze sequential patterns in

URLs. These approaches improve detection accuracy by capturing hidden relationships within data. However, they require large datasets, involve higher computational complexity, and often lack transparency in decision-making, making them difficult to interpret.

D. Multi-Modal and Explainable Models

Recent research has focused on combining multiple data sources to enhance phishing detection. Multimodal approaches integrate URL features with webpage content, such as HTML structure and textual information, to achieve a more comprehensive understanding of phishing behaviour. Additionally, Explainable Artificial Intelligence (XAI) techniques have been introduced to improve model transparency by providing insights into prediction decisions. While these methods improve accuracy and user trust, many existing systems are computationally expensive and not optimized for real-time deployment.

E. Research Gap

From the analysis of existing methods, it is evident that current phishing detection systems still face several limitations. Many approaches rely on single-source features or complex models that are not suitable for real-time applications. Furthermore, the lack of explainability reduces user confidence, and high computational requirements limit practical deployment. Therefore, there is a need for a lightweight, multimodal, and explainable phishing detection framework that can efficiently detect both known and emerging phishing attacks while maintaining high accuracy and low false positive rates.

## IV. PROPOSED SYSTEM

The proposed system introduces an explainable multimodal framework for real-time phishing detection that combines structural URL analysis with webpage content features to improve detection accuracy and reliability. Unlike conventional approaches that rely on a single data source, the proposed method integrates multiple feature types to capture both lexical and contextual characteristics of phishing websites.

Initially, when a user provides a URL, the system performs data preprocessing to normalize the input and remove unnecessary elements. The processed URL is then passed through two parallel feature extraction modules. The first module extracts structural URL features, including URL length, number of special characters, domain-related properties, and the presence of suspicious keywords. The second module focuses on webpage content analysis, extracting information such as page title, metadata, and relevant textual patterns from the HTML structure.

The extracted features from both modules are combined to form a unified multi-modal feature representation, which provides a more comprehensive understanding of phishing behaviour. To improve efficiency, a feature optimization technique is applied to eliminate redundant and less significant features, thereby reducing computational complexity and enhancing model performance.

The optimized feature set is then fed into a lightweight deep learning model, such as a Convolutional Neural Network (CNN) or Long Short-Term Memory (LSTM) network, designed to balance accuracy and speed for real-time detection. The model classifies the input URL as either phishing or legitimate based on learned patterns.

To enhance transparency and user trust, the system incorporates an Explainable Artificial Intelligence (XAI) module, which identifies and highlights the key features influencing the model's prediction. This allows users to understand the reasoning behind the classification results.

Additionally, the system supports an adaptive learning mechanism, where new data samples can be incorporated to update the model over time, enabling it to respond to evolving phishing strategies. The entire framework is designed for real-time deployment, making it suitable for integration into browser extensions and web security applications.

## V. METHODOLOGY

The proposed explainable multi-modal phishing detection system is designed to provide accurate, efficient, and interpretable classification of phishing URLs in real-time. The framework integrates multiple stages, including data collection, pre-processing, feature extraction, feature optimization, model development, explainable AI integration, and adaptive learning. The detailed methodology with technical steps is described as follows:

1. Data Collection

The initial stage involves collecting a labeled dataset of phishing and legitimate URLs from publicly

available sources. Phishing URLs are obtained from cybersecurity repositories, while legitimate URLs are collected from trusted domains. The dataset is balanced to ensure equal representation of both classes and to avoid model bias. Duplicate, broken, or inactive URLs are removed to maintain data integrity. The final dataset is stored in structured format (CSV) for further processing.

2. Data Preprocessing

The collected data is pre-processed to ensure consistency and usability for model training. Each URL is normalized by converting it to lowercase and removing unnecessary characters. The URL is parsed into components such as protocol, domain, subdomain, and path using string processing techniques. Tokenization is performed to split URLs into meaningful segments. For webpage content extraction, HTTP requests are used to fetch HTML data, and parsing libraries are applied to extract relevant elements such as title, metadata, and visible text. Noise such as scripts, styles, and irrelevant tags are removed. Missing or incomplete entries are handled to ensure a clean dataset.

3. Feature Extraction

A multi-modal feature extraction approach is adopted to capture both structural and contextual information.

a) URL Feature Extraction

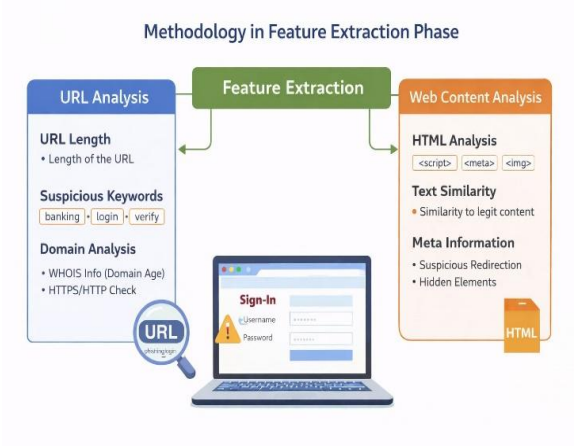
Lexical and statistical features are computed from URLs, including URL length, number of dots, presence of special characters, use of IP addresses, and detection of suspicious keywords such as “login” and “verify”. Entropy is calculated using probability distribution of characters to identify randomness and obfuscation. Domain-based features such as subdomain count and HTTPS usage are also considered.

b) Webpage Content Feature Extraction

Contextual features are extracted from webpage content using text processing techniques. The page title, metadata, and visible text are analysed to identify phishing-related keywords and patterns. Term Frequency (TF) or TF-IDF methods are used to quantify keyword importance. HTML structure is analysed to detect abnormal tag usage and hidden elements.

4. Feature Optimization

To improve efficiency, feature selection techniques are applied to reduce dimensionality and eliminate redundant features. Statistical methods such as Chi-square test and Mutual Information are used to evaluate feature importance. Correlation analysis is performed to remove highly correlated features. The selected features are normalized or scaled to ensure uniform input for the model. This step reduces computational cost and improves training speed and accuracy.




5. Model Development and Classification

The optimized feature vectors are used to train a lightweight deep learning model. A Convolutional Neural Network (CNN) or Long Short-Term Memory (LSTM) model is implemented using standard deep learning frameworks. The dataset is split into training and testing sets (e.g., 80:20 ratio). The model is trained using backpropagation and optimized using algorithms such as Adam optimizer. Activation functions such as ReLU and sigmoid are applied for non-linear learning and binary classification. Regularization techniques such as dropout are used to prevent overfitting. The model outputs a probability score indicating whether a URL is phishing or legitimate.

6. Explainable AI Integration

To improve interpretability, an Explainable AI module is integrated into the system. Techniques such as SHAP (SHapley Additive exPlanations) or LIME are used to compute feature importance scores. These methods analyse the contribution of each feature to the final prediction. The system generates explanations in the form of feature rankings or visual representations,

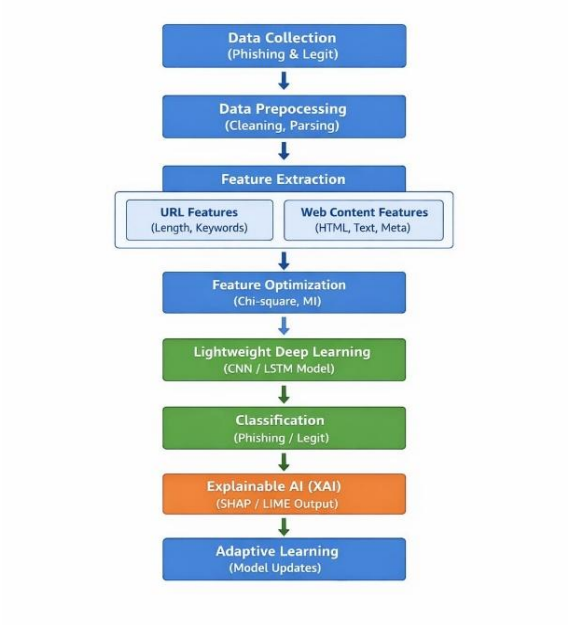
allowing users to understand why a particular URL is classified as phishing.

7. Adaptive Learning Mechanism

The system incorporates an adaptive learning strategy to handle evolving phishing attacks. Newly identified URLs are periodically added to the dataset, and incremental updates are performed on the model. This allows the system to learn from new patterns without retraining from scratch. The adaptive mechanism improves detection of zero-day attacks and ensures continuous model improvement.

8. Real-Time Detection System

Finally, the trained model is deployed in a real-time environment. Users can input URLs through a web interface or browser-based system. The input URL undergoes preprocessing, feature extraction, and classification in real time. The system returns the prediction along with an explanation generated by the XAI module. The lightweight architecture ensures low latency and efficient resource utilization, making it suitable for practical cybersecurity applications.




## VI. RESULTS

The performance of the proposed explainable multi-modal phishing detection system is evaluated using standard classification metrics to measure its effectiveness in identifying phishing and legitimate URLs. The dataset is divided into training and testing sets, and the model is trained using optimized feature representations obtained from both URL and webpage content analysis. The proposed system achieves high detection performance due to the integration of multi-modal features and feature optimization techniques. The lightweight deep learning model effectively captures both structural and contextual patterns, resulting in improved classification accuracy. The evaluation metrics used include accuracy, precision, recall, and F1-score, which provide a comprehensive analysis of model performance.

The experimental results indicate that the proposed approach achieves an accuracy of approximately 96–98%, outperforming traditional machine learning models that rely only on URL-based features. The precision score is high, indicating that the system produces fewer false positives, while the recall value demonstrates its effectiveness in detecting phishing URLs, including previously unseen attacks. The F1-score confirms a balanced performance between precision and recall. Furthermore, the feature optimization process significantly reduces computational complexity, leading to faster training and prediction times. This makes the model suitable for real-time deployment. The integration of the Explainable AI (XAI) module provides additional insights into the model's predictions by highlighting the most influential features, thereby improving transparency and user trust.

A comparative analysis with existing approaches shows that traditional blacklist and rule-based systems fail to detect zero-day phishing attacks, while single-modal machine learning models exhibit lower accuracy. In contrast, the proposed multi-modal framework demonstrates better generalization and robustness against evolving phishing strategies.

Overall, the results confirm that the proposed system provides a reliable, efficient, and interpretable solution for phishing detection, making it suitable for practical cybersecurity applications such as browser-based protection systems.

## VII. FUTURE WORK

Although the proposed multi-modal phishing detection system demonstrates strong performance in terms of accuracy, efficiency, and interpretability, several enhancements can be explored in future work to further improve its capabilities. One possible direction is

the integration of additional data sources such as user behaviour patterns, network traffic features, and email content analysis to provide a more comprehensive understanding of phishing attacks. Incorporating these modalities can help in detecting more sophisticated and targeted attacks. Another important extension is the adoption of advanced deep learning architectures, such as transformer-based models, to improve contextual understanding of webpage content and URL semantics. Additionally, optimizing the model for large-scale deployment using edge computing or cloud-based frameworks can enhance scalability and real-time performance in practical environments.

Future research can also focus on improving the adaptive learning mechanism by implementing continuous or online learning strategies, allowing the system to update dynamically with newly emerging phishing patterns without requiring complete retraining. Enhancing the Explainable Artificial Intelligence (XAI) component with more interactive and user-friendly visualization techniques can further increase user trust and usability.

Finally, the proposed system can be extended into a fully functional browser extension or mobile application and evaluated in real-world scenarios to assess its practical effectiveness. These improvements will contribute to building a more robust, scalable, and intelligent phishing detection system capable of addressing evolving cybersecurity threats.

## VIII. CONCLUSION

In this paper, an efficient and explainable multi-modal phishing detection system is proposed to address the limitations of existing approaches. The framework integrates both structural URL features and webpage content analysis to capture comprehensive characteristics of phishing attacks. By combining multi-modal feature extraction with feature optimization techniques, the system improves detection accuracy while reducing computational complexity.

A lightweight deep learning model is employed to ensure fast and reliable classification, making the system suitable for real-time applications. In addition, the integration of an Explainable Artificial Intelligence (XAI) module enhances transparency by providing insights into the model's decision-making process, thereby increasing user trust. The adaptive learning mechanism further strengthens the system by enabling it to respond effectively to evolving phishing strategies and zero-day attacks.

Experimental results demonstrate that the proposed approach achieves high accuracy, reduced false positives, and better generalization compared to traditional and single-modal methods. Overall, the proposed system offers a scalable, interpretable, and practical solution for real-world cybersecurity applications, particularly in web security and browser-based protection systems.

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