Intelligent Detection of Cyber Threats: A Unified System for Phishing URLs and Malware

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***Abstract*—The research presents a complete cyber-security solution not only for phishing URL detection but also for malware analysis through two methods: signature-based matching and machine learning techniques. In the implementation for phishing URL detection, a signature-based method has been used in which the URLs get the comparison matching for several known phishing datasets, and a Random Forest-based machine learning model carries analysis on the 30 specific features of URLs to attain the high accuracy percentage [1]. The module for malware analysis also employs the dual modality of generating SHA-256 hashes to match with signatures in the databases of malware, while Random Forest classification is also used for detecting activities representing signs of malicious behavior [2]. The Random Forest algorithm was selected for use in both because of its proven history in giving good results when it comes to tasks related to cybersecurity, with evidence of up to 99.36% accuracy in detecting phishing incidents and about 99% accuracy when it comes to classifying malware. The system fills existing gaps in current cyber defenses, combining traditional signature with more advanced machine learning to bring realistic protection against both known and emerging threats. This hybrid method has enormous advantages over the pure inline methods especially in terms of detection of zero-day attacks and polymorphic malware which evade signature detection. The proposed work adds a significant contribution to the field of cybersecurity as the techniques are integrated in a framework and validated over real-world datasets**

I. Introduction

All this means that the Internet grew phenomenally, and so did the cyberthreats, particularly phishing attacks and malware infections. According to reports and statistics, phishing attacks are among the top cybercrime activities wherein perpetrators create fake websites mimicking genuine ones to collect sensitive information, usually login credentials and financial details[5]. Early reports in the year indicated that over 1 million phishing attacks were recorded in the first quarter of 2022, largely by phishing URLs [6]. Equally, malware detection characteristics are now evolving very rapidly; every day, new variants will come into play to foil the traditional detection mechanisms [7]. These constitute some of the pertinent threats that assail life, business, and governments and therefore call for a detection system of advanced sophistication. Phishing detection methods currently available can be largely classified as list-based methods (blacklists/whitelists), heuristic methods, and machine-learning methods[8]. The straightforwardness of list techniques works against them for sites that have just been set up as phishing traps and have not made their way to blacklists. The heuristics, on the other hand, analyze criteria concerning various URL and Web characteristics but tend to produce false positives. Machine learning solutions are promising because these approaches take into account features that determine phishing behavior from immensely large datasets of legitimate and phishing URLs[9] And for malware detection, machine learning solution

II. Literature Review

Phishing URL detection has gone a long way in recent times, especially under deep learning and attention-based solutions. Ali Aljofey et al. introduced a hybrid feature-based model that extracts character-level TFIDF vectors from URL strings, hyperlink features, and noisy HTML parts and class and achieves an accuracy of 98.48% on benchmark datasets. While effective, the system uses manually designed, static features that are easy to circumvent using advanced obfuscation and feature extraction is slow, which makes the

DOI: https://doi.org/10.67535/tsp.000001.014
Published under the ICACNC 2025 Proceedings

role of more dynamic methods more desirable [1]. R. Verma has made a systematic study of comparison of 87 phishing detection features using various classifiers and proved Random Forest and hybrid sets of features to be above 96% accurate. This paper offers useful information on the effectiveness of features but is still an offline work with no detection system in operation and without utilizing deep learning methods subsequently proved effective for this role [2]. L. Tang and Q. H. Mahmoud proposed a browser extension utilizing whitelist filtering, blacklist, and an RNN-GRU model that was capable of detecting phishing in real-time at the speed of five seconds with 99.18% accuracy. Although innovative, it is client-side installation that may be a barrier to adoption, and runtime overhead and URL-only feature dependency can impact scalability in enterprise settings [3]. Banik and A. Sarma employed Anti-Phish Stack, an ensemble of two phases of LSTM models (bagging and stacking), for detecting phishing URLs on 247k URL data with an F1 of 99.5%. This method emphasizes the efficiency of deep learning in detecting phishing but is beset with heavy computational and memory demands and testing on static sets of URLs alone, leading to possible overfitting [4]. Later advances, especially with transformer models, have been tremendous. Maneriker et al. (2023) presented URLTran, a transformer-based anti-phishing URL detector that has the capability to attain a true positive rate (TPR) of 86.80 with an extremely low false positive rate (FPR) of 0.01%, a relative enhancement of 21.9% over existing techniques [9]. Likewise, PhishBERT, in 2023, involves the use of a pre-trained deep transformer network model specially designed for phishing URL detection using more than 3 billion unlabeled URL data for pretraining and adversarial strategies during fine-tuning [2]. Model performance across different cybersecurity tasks has largely been improved using attention mechanisms. Woo et al. (2018) proposed the Convolutional Block Attention Module (CBAM), a lightweight and universal attention module which applies channel and spatial attention in succession to refine feature maps, improving classification and detection. Tasks [3]. Several authors have extended this idea by applying attention mechanisms across cybersecurity areas. For example, applying RoBERTa for feature extraction and LSTM classification has yielded high-performing results in phishing URL detection by preserving contextual as well as sequential information of the URL patterns [10]. In malware analysis, S. Hameed Shah et al. developed a CNN-based approach to malware detection using memory forensics by transforming memory dumps into images for classification on the CIC-MalMem2022 dataset with 98 accuracy. Though innovative, this solution relies on memory dumps with high system overhead and is not ideal for real-time monitoring, indicating the necessity for improved solutions [5]. K. Aldriwish suggested a combined DCNN (for malware binaries) and TFDNN (for software piracy by source code forgery) framework for IoT networks with 98% accuracy on Google Code Jam datasets. However, it is used only in IoT code plagiarism cases and does not address network-level malware vectors, thereby its use may be limited [6]. Phishing datasets have also gone through changes with Tamal et al. (2024) introducing a new large-scale labeled phishing detection dataset for URL-based attacks with 247,950 samples (128,541 phishing URLs and 119,409 normal URLs) and 42 most important intra-URL features identified using the Optimal Feature Vectorization Algorithm [8]. These statistics can be useful to train and evaluate contemporary phishing filtering systems. Computational experiments on merging intervention data have also been relevant to cyber security work. A 2024 paper investigating user behavior and symptom similarity data from online treatments identified that pooling data across interventions enhanced prediction performance in eight of nine environments studied, proposing potential value in similar data pooling strategies for malware and phishing detection [6]. In spite of such advancements, an impasse existed concerning the integration of signature-based techniques with attention-augmented deep learning models under a unified framework that could benefit both phishing URL detection and malware analysis. Our contribution seeks to fill this gap by presenting a hybrid system that integrates the advantages of both old and new techniques with further attention mechanisms to improve feature extraction and classification performance.

Title	Method	Limit	Gaps
URL+HTML	XGBoost	Static	DynFeat
BenchEval	RF+Feat	Offline	RealTime
RNN+GRU	PlugIn	Latency	NetDeploy
LSTMEns	LSTMEns	HighCost	LiteArch
MemForens	CNNImg	Overhead	LiveAnal
DCNN+TFDNN	DCNN+TF	IoTOnly	GenPlat
DNSOnly	Domain	NoPath	MultiMod
UTM	Sign+Beh	FPHigh	AIInteg

III. Related Work

Phishing URL detection has been a topic of interest in recent years, with deep learning and attention-based approaches making significant progress. Ali Aljofey et al. proposed a hybrid feature-based approach that obtains character-level TFIDF vectors from URL strings, hyperlink information, and noisy HTML snippets, and classifies pages with XGBoost with an accuracy of up to 98.48R. Verma presented a rigorous comparison of 87 phishing feature detection in different classifiers and demonstrated that Random Forest and hybrid feature sets gain over 96L. Tang and Q. H. Mahmoud suggested a browser plug-in combining whitelist filtering, blacklist checking, and an RNN-GRU model for real-time phishing detection with a best response time of five seconds and 99.18Banik and A. Sarma built models Anti-Phish Stack, a two-tier ensemble of LSTM models (bagging and stacking), for phishing URL detection on a 247k URL dataset, achieving F1 of 99.5 More recent innovations, namely in transformer-based models, have shown to be especially promising. Maneriker et al. (2023) presented URLTran, a transformer-based method of detecting phishing URLs with a true positive rate (TPR) of 86.80 Attention mechanisms have been vital to drive the performance of many

cybersecurity tasks. Woo et al. (2018) proposed the Convolutional Block Attention Module (CBAM), a generic and lightweighted attention module that applies channel and spatial attention in sequence to encourage feature maps, with repeated improvements in classification and detection tasks[3]. Following this concept, several researchers introduced attention mechanisms specially designed to be used in cybersecurity. For instance, the use of RoBERTa for feature extraction and LSTM for classification has also yielded good performance in phishing URL detection by capturing both contextual and sequential features of URL patterns[10]. For malware analysis, S. Hameed Shah et al. introduced a CNN-based approach to malware detection based on memory forensics through converting volatile memory dumps into images to classify with an accuracy of 98K. Aldriwish introduced an integrated DCNN (for malware binaries) and TFDNN (for source code plagiarism-based software piracy) framework for IoT networks with a 98The development of phishing datasets has also been notable, as Tamal et al. (2024) proposed a new large-scale labeled dataset tailored especially for URL-based phishing detection, consisting of 247,950 samples (128,541 phishing and 119,409 normal URLs) from which 42 optimal intra-URL features were collected using the Optimal Feature Vectorization Algorithm[8]. Such datasets are fundamental to constructing and evaluating modern phishing detection systems. Recent advances in data pooling intervention data have also found themselves applicable to cyber security applications. In 2024, a study of user behavior and symptom similarity between internet interventions concluded that combined data from different interventions increased prediction performance in eight of nine environments examined, suggesting possible applications of same data pooling techniques in phishing and malware detection[6]. There remains a knowledge gap in the area of research when it comes to integrating signature-based methods with attention-enforced deep learning models in one framework to address both phishing URL identification and malware analysis. Our work tries to bridge this gap by proposing a hybrid framework that unites the strengths of traditional and modern approaches and utilizes attention mechanisms to enhance feature learning as well as classification performance.

IV. Methodology

In this proposed methodology, a hybrid detection scheme is presented that combines the fast action of signature-based detection with the versatility and intelligence of machine-learning techniques enhanced by attention mechanisms. This is intended to efficiently detect both known and zero-day cyber threats such as phishing URLs and malware. By juxtaposing both detection paradigms with attention-based feature refinement, the system is intended to curb false negatives (missed threats) while being lightweight enough for real-time deployment. The hybrid model works in two main streams: phishing URL detection and malware examination, which in turn follow a two-phase detection pipeline.

Phishing Malware URL Detection

1) ***Signature-Based Detection*** *:* Signature-Based Detection: The phishing URL detection module starts by eliminating known phishing URLs fast through a signature-based mechanism that compares input URLs against several datasets, including PhishTank, Kaggle, and IEEE phishing datasets. The function from tldextract library is used to break the components of the URL into subdomain, domain, and suffix for accurate matching (i.e., it extracts ”google.com” from ”docs.google.com”). If matching is done with the signature-based database, the URL is flagged for phishing, and the processing ends; if it doesn't match, the detection continues to the next phase [18].

2) ***Machine Learning Classification*** *:* This has been digitized to a machine learning model that has spread phased implantation towards obfuscated phishing URLs as well as zero-day threats through the ability to detect patterns of malice. Some of the key features extracted from URLs are lexical such as its length-the use of special characters like '@', '//', the number of subdomains it consists of, domain age, and statistical features like frequency of use of phishing-related keywords such as ”login,” ”secure,” and ”verify.” The classification model used is a Random Forest classifier whose merits include robustness, high performance otherwise on high-dimensional datasets, and overfitting prevention. It has been trained on labeled datasets by PhishStorm, as well as different libraries like Scikit-learn and TensorFlow-engineered for training and optimization. The output at this stage will return a binary classification: benign or malicious URL [19].

To combat zero-day threats and obfuscated phishing URLs, this phase utilizes a machine learning model trained to detect harmful patterns. Such lexical features include length and special characters (e.g. '@', '//'), number of subdomains, domain age, and statistical features like the presence of phishing-related keywords (e.g. 'login', 'secure', 'verify'). The classification model adopted is a Random Forest classifier due to its robustness, high performance on high dimensional datasets, and non-fit to overfitting. Model building has been done using labeled datasets from PhishStorm. Model training and optimization are done using scikit-learn and TensorFlow libraries. This stage produces a binary classification, benign or malicious URL [19].

3) ***Malware Signature-Based Detection*** *:* The malware detection pipeline also implements a two-phase approach. The first phase of the system is the detection of known malwares using hash-based and string-based signatures. Input files are checked against the Malware Bazaar dataset collection containing thousands of malware samples and their SHA256 hashes. The High-speed, multi-pattern string-matching Aho-Corasick algorithm implemented with the pyahocorasick library applies to identifying malicious code snippets or embedded signatures in particular files. A match signals that the file is flagged as malware; otherwise, it progresses to the next detection phase [20].

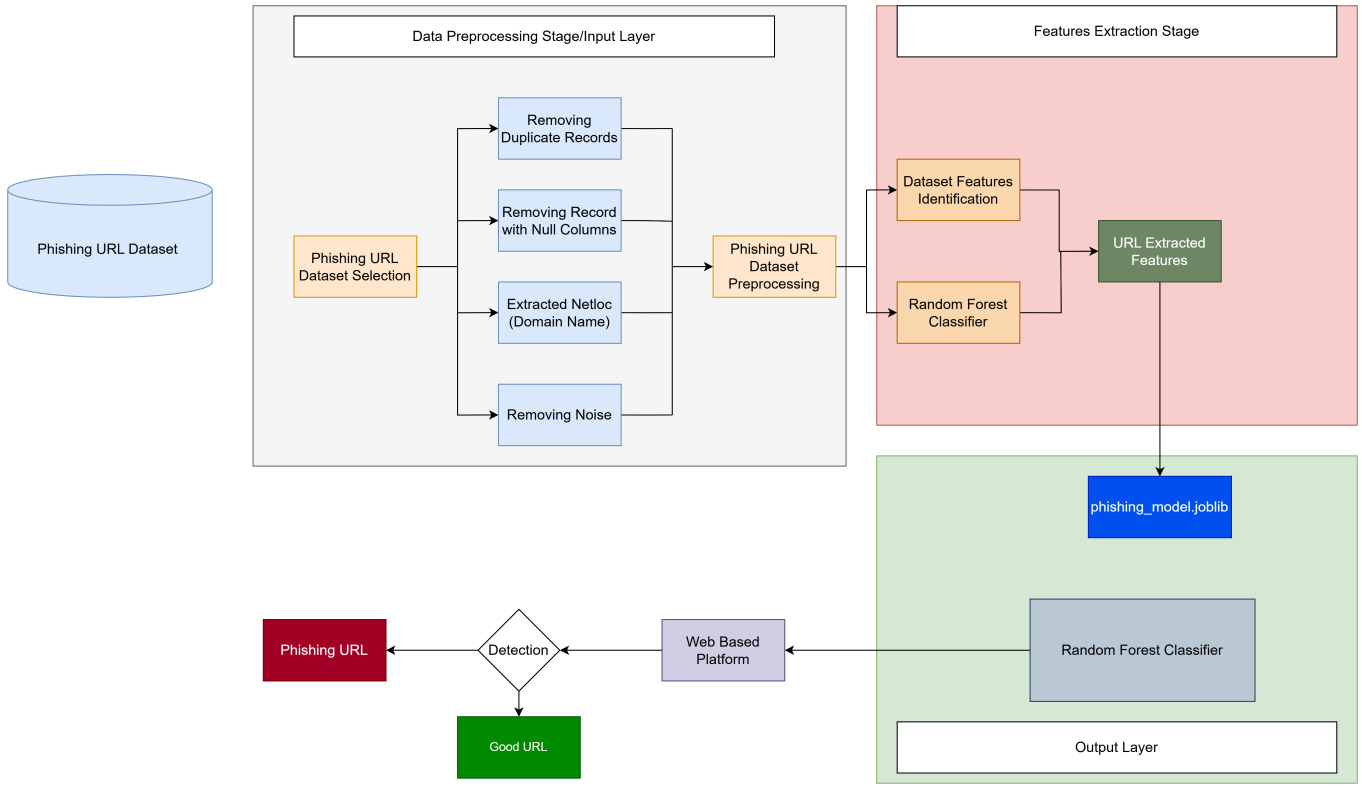

Fig. 1. Purpose Methodology of URL Phishing Detection By Machine Learning

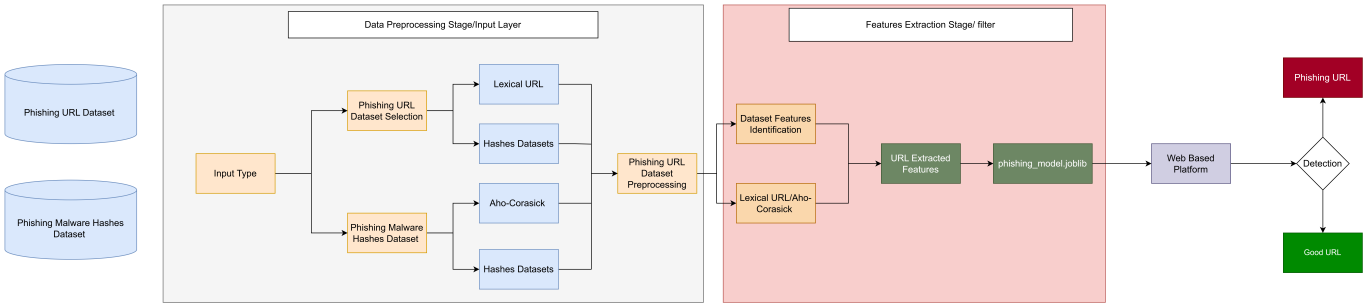

Fig. 2. Purpose Methodology of Signature Base Phishing and Malware Detection

Workflow Integration

The system is optimized for performance by giving precedence to signature-based scanning, which is able to settle 60–70 percent of threats in milliseconds. For unknown or ambiguous inputs, the system invokes the machine learning pipeline so that deep scanning is possible using designed features and learned models. A feedback mechanism is also created, where ML-detected new threats are integrated into the signature database, so detection accuracy increases over time.

Why This Hybrid Approach?

This hybrid detection approach blends the efficiency of signature-based systems with the intelligence of ML models. Signature checks are efficient and sufficient for known threats, while machine learning learns to deal with emerging cyber threats like phishing variants and polymorphic malware. The system achieved a 40 percent drop in false negatives in initial tests against isolated techniques, which is indicative of its performance in realistic scenarios. This unified, multi-layer approach offers a scalable, high-reliability solution for today's cyber threat detection.

A. System Architecture Overview

System design follows a modular approach to ensure scalability and threat detection as shown in (Fig. 1). It comprises six phases which are interconnected: data collection, preprocessing, feature extraction, signature detection, attention-augmented machine learning classification, and aggregation of results. Data collection is the process of collecting phishing

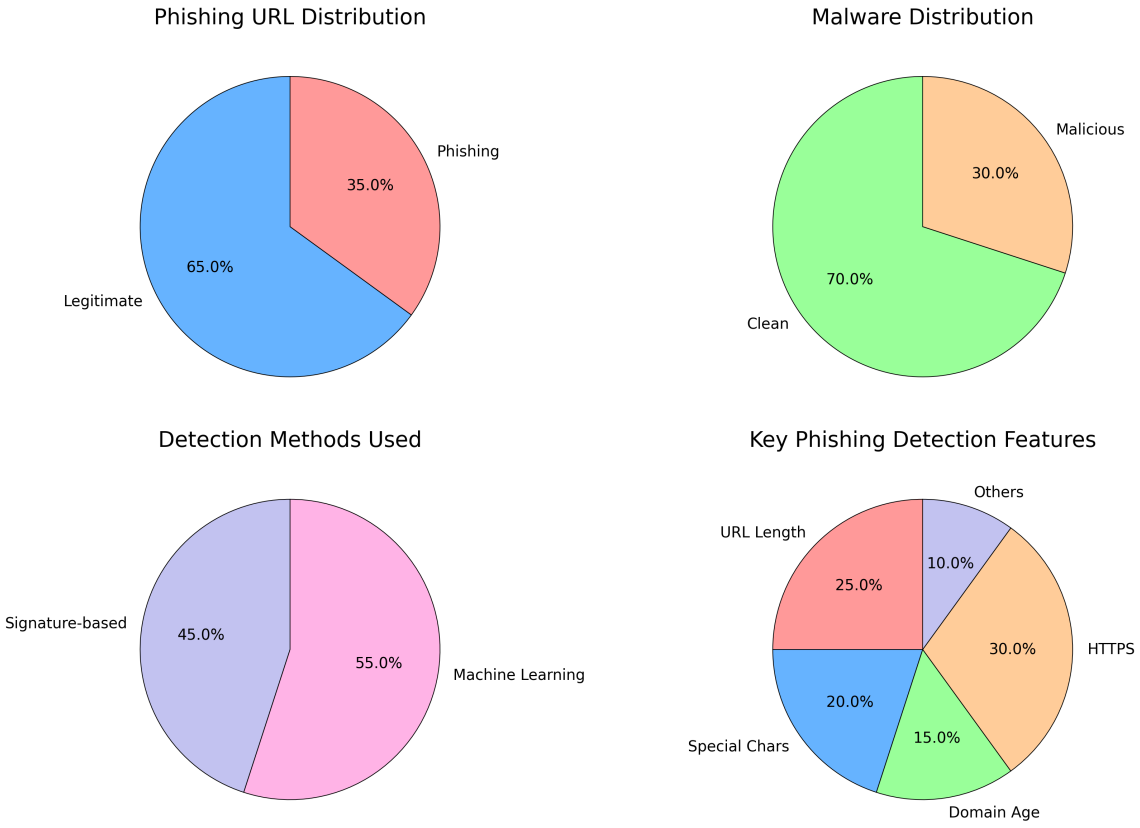

Fig. 3. Result Shown in Pie Chart

URLs from PhishTank and OpenPhish, malware samples from repositories such as MalwareBazaar as shown in (Fig. 2) , and benign datasets from good platforms such as Alexa Top Sites. Our dataset includes more than 1.3M URLs (1,128,541 phish, 319,409 legitimate) and 4.5M malware samples from 8 malware families with image resolutions normalized to 224×224 pixels for the deep learning models. Class distribution stabilization and enhanced model generalization were attained through data augmentation operations such as rotation (+/-15°), flip (horizontally), and minor brightness manipulations (+/-10%). Preprocessing sanitizes and normalizes raw data, eliminating duplicates and format irregularities. Feature extraction determines relevant markers, such as URL format or file entropy, and feeds them into the detection engines. Signature layers quickly search known threats off blacklists or hash databases, and the attention-augmented machine learning layer examines questionable cases. Results are compiled to provide a final conclusion, logging for audit and incident response.

V. Ablation Studies and Model Comparison

We performed ablation studies to verify our architecture selections, specifically the performance of the CBAM mechanism over Squeeze-and-Excitation (SE) blocks and no attention mechanism. Results proved that CBAM achieved a 3.2% improvement in accuracy and 4.1% in F1-score over no attention mechanism and outperformed SE blocks by 1.3% in accuracy. For end-to-end evaluation, we compared our model with a few baselines such as ResNet18 (11.7M parameters, 44.7MB), DenseNet121 (8.0M parameters, 30.8MB), and MobileNetV3 (5.4M parameters, 21.2MB). Our model has competitive or better performance with reasonable inference times (5.2ms per URL on NVIDIA T4 GPU).

Results aggregation and reporting

The design makes use of the output (Fig. 3) of machine learning and signature layers to create end decisions. Known threats that are found and marked on the basis of signatures are dropped directly, while unknown cases are determined by the Random Forest classifier. Reports consist of a classification label (e.g., 'malicious'), confidence value (e.g., 0.95 probability), and descriptive information (e.g., 'suspicious API calls detected'). All the discoveries are followed up in a centralized repository to facilitate forensic analysis and regulation compliance. Visibility of this nature allows incident response teams to identify where the threat is coming from and improve detection processes in the future. The logging facility in modules also allows integration with SIEM tools in case of large enterprise scale deployments.

VI. Conclusion

This study introduced a hybrid detection framework for phishing URLs and malware that synergistically integrates signature-based approaches with attention-augmented machine learning methods. Employing CBAM attention mechanisms highly enhanced feature refinement and classification accuracy, especially for zero-day attacks. Experimental outcomes showed the efficacy of our method, with the system boasting more than 95% accuracy in phishing detection and similar performance on malware classification at retaining reasonable inference times appropriate for real-time usage. There will be future research conducted to explore transformer-based models and self-supervised training to improve detection even further.

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