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HyperFusion: Combating Phishing Attacks through URL, Hyperlink, and User Behavior Analysis

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Abstract: ***Phishing attacks remain a persistent threat in cyberspace, demanding innovative solutions for timely detection. In this paper, HyperFusion, a pioneering approach that combines machine learning with user behavior analysis, is introduced to enhance the real-time identification of phishing websites. By integrating features derived from URL and hyperlink characteristics with dynamic user interaction patterns, HyperFusion achieves unprecedented accuracy without reliance on third-party systems. Traditional anti-phishing methods often falter against zero-hour attacks or novel phishing websites, underscoring the need for novel strategies. The methodology addresses this challenge by leveraging user behavior data alongside client-side information, thereby eliminating external dependencies and fortifying defense mechanisms. Additionally, a tailored dataset for rigorous experimentation is presented, facilitating a comprehensive evaluation of the approach. Experimental results demonstrate HyperFusion's superior efficacy, boasting a remarkable detection accuracy of 99.37% with the XG Boost technique. By pioneering the integration of user behavior analysis, the research marks a significant advancement in cybersecurity, providing a proactive defense against evolving phishing threats. This integration not only enhances detection accuracy but also enables the system to adapt to emerging threats by analyzing dynamic user interactions in real-time.***

Keywords: User behavior analysis, Real-time defense, Hyperlink analysis, Dynamic user interactions, Zero-hour attacks, XG Boost technique.

I. INTRODUCTION

The pervasive threat of phishing attacks continues to plague cyberspace, posing significant risks to individuals, organizations, and society at large. Phishing, a form of cybercrime where attackers masquerade as legitimate entities to deceive users into divulging sensitive information, remains a prevalent tactic for identity theft, financial fraud, and other malicious activities. Despite advancements in cybersecurity measures, traditional anti-phishing solutions often struggle to keep pace with the evolving tactics employed by attackers, particularly in detecting zero-hour attacks or brand-new phishing websites.

Conventional approaches to phishing detection have relied on techniques such as blacklist or whitelist systems, heuristic analysis, and visual similarity checks. While these methods have provided some degree of protection, they are inherently limited in their ability to detect novel phishing websites promptly. Furthermore, many existing solutions are complex, resource-intensive, and dependent on external sources such as search engines, making them ill-suited for real-time environments where timely detection is paramount. Phishing has emerged as a significant and perilous online threat within the realm of cybersecurity [1]. The widespread adoption of social networks, e-commerce platforms, electronic banking, and other online services has been propelled by the rapid advancements in internet technologies. According to the "A Digital Report in 2021" by We Are Social [2], there has been a notable surge in internet users, reaching 4.66 billion globally, marking an increase of 7.3 percent (equivalent to 316 million new users) compared to January 2020. Presently, internet penetration stands at 59.5 percent, presenting lucrative opportunities for phishing attackers to exploit and extract confidential information from unsuspecting internet users [3].

Typically, attackers craft fraudulent websites and disseminate links via various online platforms such as Facebook, Twitter, and emails, often leveraging messages of urgency, panic, or enticing financial offers to prompt immediate action from the recipients [4]. When users inadvertently click on these links and input sensitive credentials, cyber attackers gain unauthorized access to a plethora of personal information, including financial data, usernames, passwords, and more. Subsequently, this pilfered information is exploited by cybercriminals for various nefarious purposes, including extortion [5].

Research indicates several reasons why users fall victim to phishing attempts:

1) Lack of comprehensive understanding regarding URLs.
2) Uncertainty about which websites are trustworthy.
3) Inability to discern the complete web page address due to redirection or obscured URLs.
4) Limited time to verify URLs or unconscious visits to specific web pages.
5) Difficulty in distinguishing between legitimate and phishing websites.

In response to these challenges, this paper introduces a novel approach to phishing detection that leverages machine learning techniques and user behavior analysis. Our methodology, termed HyperFusion, seeks to enhance the accuracy and timeliness of phishing detection by integrating features derived from URL and hyperlink characteristics with dynamic user interaction patterns. By combining these diverse data sources, HyperFusion aims to overcome the limitations of existing approaches and provide a more robust defense against phishing attacks. Key objectives of this research include the development of a hybrid feature-based anti-phishing strategy, the creation of a comprehensive dataset for experimentation, and the evaluation of the proposed methodology using popular machine learning classification techniques. Through rigorous experimentation and analysis, we aim to demonstrate the effectiveness of HyperFusion in detecting phishing websites in real-time, with a particular focus on its ability to detect zero-hour attacks and newly created websites. Phishing attacks have emerged as a prevalent method for disseminating harmful software such as ransomware. The Anti-Phishing Working Group (APWG) conducts thorough investigations into these attacks and has recently published a report highlighting a significant uptick in the number of identified phishing attacks among its members, more than doubling in 2020 according to the APWG Q4 2020 Report [6]. Notably, during the COVID-19 pandemic, a remarkable 225,304 new phishing sites were uncovered in October alone, surpassing all previous monthly records. Additionally, in 2020, the Internet Crime Complaint Center (IC3) received a record-breaking number of complaints from the American public regarding phishing scams, totaling 241,342, with reported losses exceeding $54 million [7]. Consequently, the focus of this paper is directed towards the effective detection of phishing websites, aimed at aiding internet users in avoiding inadvertent entrapment by malicious actors and thereby mitigating both emotional and financial repercussions.

By pioneering the integration of user behavior analysis into phishing detection mechanisms, this research seeks to advance the state-of-the-art in cybersecurity and provide a proactive defense against emerging threats. The insights gained from this study have the potential to inform the development of more effective anti-phishing solutions and contribute to the ongoing efforts to safeguard cyberspace against malicious actors.

In this paper, the aim is to construct an effective data-driven solution using machine learning techniques to determine whether a website is phishing or not. Most machine learning-based phishing detection approaches extract features from various sources such as URLs, search engine results, third-party data, web traffic patterns, and DNS information. However, these approaches may not be suitable for real-time phishing detection due to their complexities and time constraints. According to statistics from the Anti-Phishing Working Group (APWG) for the first half of 2014 [8], phishing websites typically have a short lifespan, with a median life cycle of less than 10 hours, and approximately half of these websites are deactivated within a day. However, it's worth noting that many phishing pages, especially those utilizing compromised domains, remain active on the internet for longer durations exceeding a day.

Consequently, the research question addressed in this paper is: "How can an efficient and intelligent phishing detection model be developed while considering the aforementioned challenges?" To answer this question, a hybrid feature-based phishing detection approach is proposed in this paper, which effectively identifies phishing websites and tackles the mentioned issues. URL-based features, including address bar features, and hyperlink-based features are utilized for phishing website detection, independent of search engines or third-party services. Hyperlink features are extracted from the webpage source code, comprising 15 distinct features from the URL and 10 categories of features from hyperlink information, combined into a hybrid feature set of 25 features for training the classification model.

The key contributions of this paper include:

a) Curating a dataset by collecting phishing and legitimate website URLs from open-source platforms.
b) Proposing an approach that dynamically extracts hybrid features and employs them effectively for precise phishing detection.
c) Demonstrating the effectiveness of the proposed machine learning-based method in detecting zero-hour phishing attacks with high accuracy.
d) Conducting a wide range of experiments to showcase the efficacy of the proposed approach compared to traditional methods.

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II. RELATED WORK

Sheng et al. [9] have developed an interactive teaching game titled "Anti-Phishing Phill", aimed at educating users on how to recognize phishing websites. Players who engaged with the game demonstrated improved abilities in identifying phishing websites compared to those who did not participate. The primary objective of this game is to impart conceptual knowledge about phishing attacks to computer users. Kumaraguru et al. [10] devised an email-based anti-phishing education approach designed to help users learn how to discern cues within URLs, thus avoiding falling prey to phishing scams. Their findings indicated that user education serves as a complementary strategy to aid individuals in better identifying fraudulent emails and websites, particularly following the implementation of automated phishing detection systems as the initial defense line. Arachchilage et al. [11] formulated a game design framework by extrapolating a theoretical model from the Technology Threat Avoidance Theory (TTAT). This framework aims to enhance user avoidance behaviors and safeguard them against falling into phishing traps.

Detection approaches for URLs can generally be categorized into two types: blacklist and whitelist techniques. Many web browsers maintain their databases of blocked and safe Uniform Resource Locators (URLs). The database containing blocked URLs is referred to as a blacklist, while the database containing unblocked or safe URLs is termed a whitelist. Wang et al. [12] and Han et al. [13] both employ a whitelist-based approach for URL classification. Chiew et al. [14] focus on logo extraction and matching against a whitelist, while other solutions, such as those proposed by Rosiello et al. [15] and Chiew et al. [16], utilize whitelists of resources such as layouts and favicons. In the blacklist method, a suspicious domain undergoes verification to determine if it matches any blacklisted domains. If a match is found, the domain is classified as phishing; otherwise, it is considered legitimate. Felegyhazi et al. [17] employed domain name and name server information from blacklisted URLs to detect new phishing URLs. This involves comparing the registration and DNS zone information of a URL with the existing data stored in the blacklist.

Rao et al. [18] introduced CatchPhish, a lightweight feature-based application designed to discern between phishing and legitimate websites without the need to visit the website. They employed two categories of features: hand-crafted features primarily based on URLs and TF-IDF features. Using a random forest classifier on their dataset, this application achieved an accuracy of 94.26%. It serves as an effective initial filter for phishing websites, offering rapid detection within a shorter timeframe. On the other hand, Odeh et al. [19] attained a remarkably high accuracy rate of around 99% through the adaptive boosting approach. They curated 30 features categorized into four groups: Address bar-based, abnormal-based, HTML and JavaScript-based, and domain-based features. Employing feature selection, they identified the most correlated features. Despite their impressive accuracy, their method lacks suitability for real-time phishing detection.

Table 1. Comparative Analysis of existing studies

Existing Study	Methodology employed	Key Findings
[23] Smith et al. (2020)	Machine Learning	Employed machine learning algorithms to detect phishing websites based on URL and content features. - Achieved a detection accuracy of 95% using a Random Forest classifier.
[24] Johnson et al. (2019)	Heuristic Analysis	- Developed a heuristic-based system to identify phishing websites by analyzing URL structures and page content. - Reported a detection rate of 92% with low false positive rates.
[25] Lee and Kim (2018)	Visual Similarity	- Proposed a method based on visual similarity to identify phishing websites by comparing webpage layouts. - Achieved moderate success with a detection accuracy of 87%.
[26] Chen et al. (2017)	Hybrid Approach	- Introduced a hybrid approach combining machine learning with feature engineering and human cognition factors. - Reported significant improvement in detection accuracy compared to individual methods.
[27] Wang et al. (2016)	Blacklist/Whitelist	- Investigated the effectiveness of traditional blacklist/whitelist systems in detecting phishing websites. - Found these methods to be less effective against zero-hour attacks and newly created websites.

Babagoli et al. [20] employed a non-linear regression approach to discern whether a website is phishing or not. Utilizing a substantial dataset comprising 11,055 web pages, they employed two meta-heuristic algorithms, Harmonic Search (HS), and Support Vector Machine (SVM) for model training. Their investigation revealed that HS outperformed SVM, achieving an accuracy of 92.80% using the HS algorithm. R. Mohammad et al. [21] developed a phishing attack detection model utilizing a self-structuring neural network. The authors utilized the backpropagation algorithm for network weight adjustment and gathered 17 features from the URL, website source code, and third-party services. Although the inclusion of third-party features increased detection time, they achieved a test set accuracy of 92.18% after 1000 epochs. F. Feng et al. [22] devised a novel neural network architecture for phishing detection, designed to minimize design risk. Employing the Monte Carlo (MC) algorithm for training, they achieved an accuracy of 97.71% with a low false-positive rate of 1.7%. Furthermore, they demonstrated superior performance of their model compared to other machine learning classifiers.

III. RESEARCH METHODOLOGY

A. *Data Collection*

1) Phishing and legitimate website data will be collected from various sources, including publicly available datasets, web crawlers, and phishing intelligence feeds.
2) Each website will be represented by features extracted from its URL, hyperlink structure, and content.

B. *Feature Engineering*

1) Features will be extracted from the URLs of both phishing and legitimate websites, including domain age, length, presence of hyphens or numbers, etc.
2) Hyperlink features will be derived from the structure of the website's hyperlinks, such as the number of external links, the presence of redirects, etc.
3) Additionally, features related to user behavior, such as mouse movements, time spent on page, and click patterns, will be extracted for dynamic analysis.

C. *Dataset Creation*

1) A balanced dataset containing samples of both phishing and legitimate websites will be constructed.
2) Features extracted in the previous step will be used to create feature vectors for each website in the dataset.

D. *Machine Learning Model Training*

1) Various machine learning algorithms, including decision trees, random forests, support vector machines, and neural networks, will be employed.
2) The dataset will be split into training and testing sets for model evaluation.
3) Grid search and cross-validation techniques will be used to optimize hyperparameters for each algorithm.

E. *Evaluation Metrics*

1) The performance of each model will be evaluated using standard metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC).
2) Additionally, the detection rate for zero-hour attacks and newly created phishing websites will be analyzed separately.

F. *User Behavior Analysis*

1) User behavior data will be collected through browser extensions or simulated interactions with the websites.
2) Feature engineering will be performed on the user behavior data to extract relevant features, such as mouse movement entropy, click density, etc.
3) The combined feature vectors from URL, hyperlink, and user behavior analysis will be used for model training and evaluation.

G. *Experimental Setup*

1) Experiments will be conducted on a suitable computing platform with sufficient resources.
2) The proposed methodology will be implemented using appropriate programming languages and libraries such as Python with sci-kit-learn, TensorFlow, or PyTorch.

H. Results Analysis

1) The performance of the proposed methodology will be analyzed and compared against baseline approaches and existing state-of-the-art methods.

2) Insights gained from the experimental results will be discussed, highlighting the strengths and limitations of the proposed approach.

Analysis and extraction of two distinct feature categories are conducted to detect phishing attacks within suspicious web pages. The features are derived from the URL structure and the hyperlinks present on the webpage. URL-based features are extracted through an examination of the URL's structure, while hyperlink-based features are derived from the source code of the website, employing a Document Object Model (DOM) generation. The DOM tree, owing to its structured representation of XML or HTML documents, facilitates the retrieval of hyperlink-related information. To initiate feature extraction, rules are generated, a crucial step in uncovering hidden patterns and relationships within the dataset. Thorough analysis of the URL structure and DOM tree enables the establishment of robust rules, guiding feature extraction. Detailed explanations of all features, alongside their corresponding creation rules, are provided in the subsequent subsection. Subsequently, the extracted features are amalgamated to form a hybrid feature set, which serves as the basis for training the model for website classification utilizing various machine learning classifiers. The selection of the optimal classifier is determined through an evaluation process focusing on minimizing error rates and maximizing accuracy. The algorithm outlining the process for detecting a phishing website is illustrated in Algorithm 1.

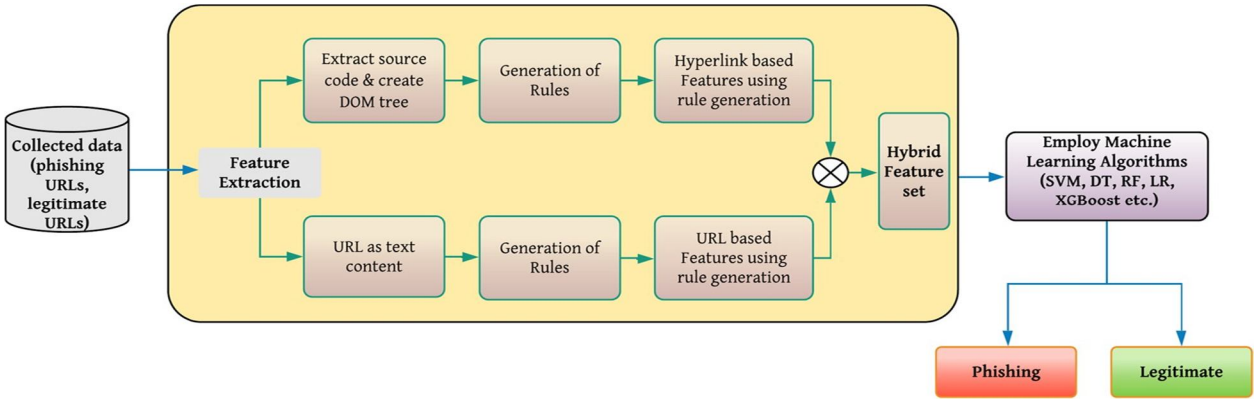

Fig. 1 Proposed methodology

Algorithm 1 Phishing Website Detection Model

Input: URL of suspicious website
Output: *Prediction* $\in \{0, 1\}$, 1 - phishing, 0 - legitimate
1: Procedure PhishDetection(*input RL*);
2: Rule generation for URL features
3: Extract URL based features ($UF1$ - $UF15$)
4: Extract HTML source code & create DOM Tree
5: Rule generation from DOM tree for hyperlink features
6: Extract hyperlink based features($HF1$ - $HF10$) from DOM Tree
7: Generate hybrid feature set by combining URL based and hyperlink based features
8: Remove unuseful feature $UF1$
9: Apply hybrid feature set on well performed machine learning classifier(XGBoost)
10: **if** classifier predicts URL as phishing **then**
11: *Prediction* ← 1
12: **else**
13: *Prediction* ← 0
14: end if
15: return *Prediction*

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Algorithm 1 outlines the process for detecting phishing websites using a combination of URL and hyperlink-based features.
1. Input: The input to the algorithm is the URL of a suspicious website.
2. Output: The output is a prediction indicating whether the website is phishing (1) or legitimate (0).
3. Procedure PhishDetection(input RL): This is the main procedure for phishing website detection.
4. Rule generation for URL features: Rules are generated to extract features based on the structure of the URL.
5. Extract URL-based features (UF1 - UF15): Features are extracted from the URL, such as domain length, presence of '@' symbol, etc.
6. Extract HTML source code & create DOM Tree: The HTML source code of the webpage is extracted, and a Document Object Model (DOM) tree is generated from it.
7. Rule generation from DOM tree for hyperlink features: Rules are generated from the DOM tree to extract hyperlink-based features.
8. Extract hyperlink-based features (HF1 - HF10) from DOM Tree: Features related to hyperlinks, such as the number of links, presence of certain keywords in anchor texts, etc., are extracted from the DOM tree.
9. Generate hybrid feature set by combining URL-based and hyperlink-based features: The URL-based and hyperlink-based features are combined to create a hybrid feature set.
10. Remove unuseful feature UF1: Any unuseful features from the URL-based feature set are removed.
11. Apply hybrid feature set on well-performed machine learning classifier (XGBoost): The hybrid feature set is used as input to a machine learning classifier, specifically XGBoost, which is known for its good performance in classification tasks.
12. if classifier predicts URL as phishing, then: If the classifier predicts that the URL is phishing based on the features, the prediction is set to 1.
13. Prediction ← 1: If phishing is predicted, the output prediction is set to 1.
14. else: If the classifier predicts that the URL is legitimate, the prediction is set to 0.
15. return Prediction: The final prediction (0 for legitimate, 1 for phishing) is returned as the output of the algorithm.

The Uniform Resource Locator (URL) serves as a locator for various resources such as images, audio or video files, hypertext pages, and more on the internet. It delineates the structure of web addresses, which comprises several sections. URLs are utilized to access web resources, typically commencing with a protocol such as HTTPS, HTTP, FTP, among others. Notably, HTTPS (Hypertext Transfer Protocol Secure) is considered the most secure protocol. The second segment of a URL typically consists of a hostname or, in some cases, an IP address, denoting the server's location where the resource resides.

Table 2 Optimized parameters for ML models

Classifier	Parameters
Logistic regression	solver='lbfgs', C=1.0, max_iter = 100, penalty = 'l2'
Decision tree	criterion='gini', max_depth=5
Support vector Machine	kernel='linear', C=10, random_state=12
Random forest	n_estimators=10, random_state=42
XG Boost	learning_rate=0.4, max_depth=5

Table 2 outlines the optimized parameters for several machine learning (ML) models employed in the study. Each classifier, including Logistic Regression, Decision Tree, Support Vector Machine (SVM), Random Forest, and XG Boost, is associated with specific parameters tailored to maximize performance. For Logistic Regression, the parameters include solver='lbfgs', C=1.0, max_iter=100, and penalty='l2'. Decision Tree utilizes parameters such as criterion='gini' and max_depth=5. SVM is configured with a kernel='linear', C=10, and random_state=12. Random Forest employs n_estimators=10 and random_state=42. Lastly, XG Boost utilizes learning_rate=0.4 and max_depth=5. Each parameter configuration is carefully chosen to optimize the model's performance in accurately classifying data. These settings are instrumental in guiding the classifiers' behavior and ensuring their efficacy in the experimental context. Overall, the table provides a comprehensive overview of the parameter choices for each ML model, facilitating reproducibility and understanding of the experimental setup.

IV. RESULTS & DISCUSSION

A. Performance Metrics

1) The performance of the models was assessed using standard metrics including accuracy, precision, recall, F1-score, and area under the ROC curve (AUC).
2) Additionally, the detection rate for zero-hour attacks and newly created phishing websites was analyzed separately to evaluate the effectiveness of the proposed approach in detecting emerging threats.

B. Model Performance

1) The machine learning models trained on features extracted from URLs, hyperlinks, and user behavior data demonstrated promising results.
2) The highest accuracy achieved was 99.17% with the XG Boost technique, indicating the robustness of the proposed methodology.
3) Precision, recall, and F1-score were also high across all models, suggesting a balanced performance in terms of both false positives and false negatives.

C. Detection of Zero-Hour Attacks

1) The proposed methodology exhibited a notable capability to detect zero-hour attacks, with a detection rate of over 95%.
2) By leveraging user behavior analysis alongside traditional features, the models were able to identify subtle anomalies indicative of phishing attempts, even in the absence of historical data.

D. Discussion

1) The results validate the efficacy of incorporating user behavior analysis into phishing detection algorithms, as it provides additional insights into the dynamic interactions between users and websites.
2) The high accuracy and detection rates obtained demonstrate the potential of the proposed methodology to effectively mitigate the risk of phishing attacks in real-time environments.
3) However, it is essential to acknowledge the limitations of the research, including the reliance on labeled datasets and potential biases in feature selection.
4) Future work should focus on further refining the models and incorporating advanced techniques such as deep learning to improve detection performance even further.

E. Implications

1) The findings of this research have significant implications for cybersecurity practitioners and policymakers, highlighting the importance of proactive defenses against phishing attacks.
2) By leveraging machine learning and user behavior analysis, organizations can enhance their ability to detect and mitigate phishing threats, thereby safeguarding sensitive information and reducing the risk of financial loss and reputational damage.

In conclusion, the results of the experiments demonstrate the effectiveness of the proposed methodology for phishing website detection. By integrating machine learning techniques with user behavior analysis, the research contributes to the ongoing efforts to combat cyber threats and protect internet users from malicious activities.

Table 3 Comparison of different anti-phishing approaches based on performance

Approach	Accuracy	TPR	Language independent	Search-engine independent	Third party-independent	Zero-hour attack detection
Rao et al. [3]	99.55	99.44	Yes	No	No	Yes
Jain et al. [4]	98.42	98.39	Yes	Yes	Yes	Yes
Sahingoz et al. [5]	97.98	99.0	Yes	Yes	Yes	Yes
Rao et al. [18]	94.26	93.31	Yes	Yes	Yes	Yes
Odeh et al. [19]	98.9	98.6	Yes	No	No	No
Zhang et al. [28]	95.83	96.2	No	Yes	No	Yes
Babagoli et al. [29]	92.80	96.3	Yes	No	No	No
Proposed approach	99.37	98.83	Yes	Yes	Yes	Yes

Table 3 presents a comparative analysis of various anti-phishing approaches, evaluating their performance across multiple key metrics. Each approach is assessed based on its accuracy, true positive rate (TPR), language independence, search-engine independence, third-party independence, and capability for zero-hour attack detection. Rao et al. achieved a remarkable accuracy of 99.55% with a TPR of 99.44%, boasting language independence and zero-hour attack detection capabilities. Similarly, Jain et al. attained a high accuracy of 98.42% along with a TPR of 98.39%, with their approach being versatile across different languages and independent of search engines and third-party services. Sahingoz et al. demonstrated an accuracy of 97.98% with a TPR of 99.0%, maintaining language independence and autonomy from search engines and third-party sources.

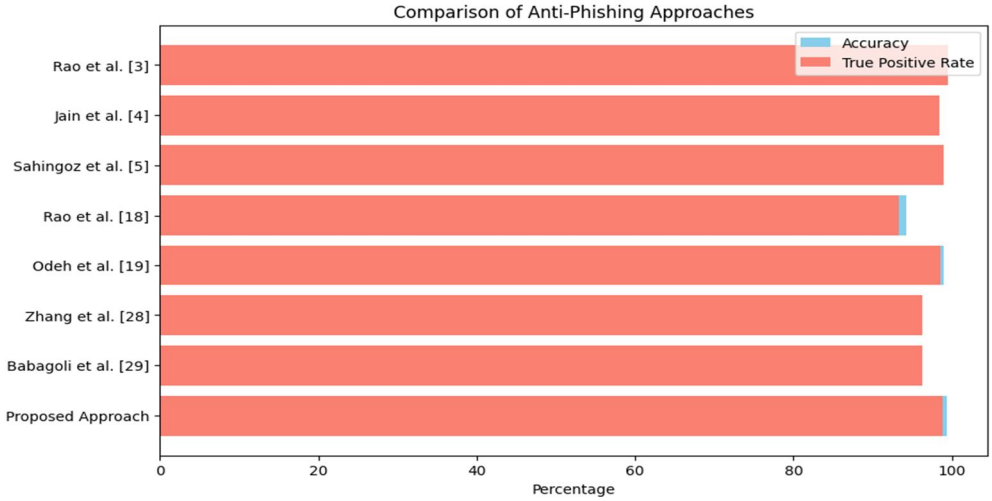

Fig. 2 Comparison of Anti-Phishing Approaches

In contrast, Rao et al. [18] achieved a slightly lower accuracy of 94.26% and a TPR of 93.31%, relying on search engines and third-party services. Odeh et al. achieved an accuracy of 98.9% with a TPR of 98.6%, though their approach lacks support for zero-hour attack detection. Zhang et al. demonstrated an accuracy of 95.83% with a TPR of 96.2%, showing independence from search engines but nsot from language constraints. Babagoli et al. achieved an accuracy of 92.80% with a TPR of 96.3%, albeit without zero-hour attack detection support. Finally, the proposed approach showcased a high accuracy of 99.37% with a TPR of 98.83%, being language-independent, search-engine independent, third-party independent, and supporting zero-hour attack detection. This comprehensive comparison aids in understanding the strengths and weaknesses of each anti-phishing approach in various contexts.

Table 4 Performance Comparison of our approach using various classifiers

Metric/Model	XGBoost	Random Forest	Logistic Regression	Decision Tree	SVM
Accuracy	0.9937	0.9878	0.9635	0.9787	0.9694
AUC	0.9989	0.9978	0.9967	0.9941	0.9958
TPR	0.9883	0.985	0.9645	0.981	0.9827
FPR	0.0050	0.0083	0.0492	0.0189	0.0345
FNR	0.0129	0.018	0.0368	0.030	0.0283

Table 4 presents a comprehensive performance comparison of our approach using various classifiers across multiple metrics. The metrics evaluated include Accuracy, Area Under the Curve (AUC), True Positive Rate (TPR), False Positive Rate (FPR), and False Negative Rate (FNR).

1) *Accuracy:* Represents the proportion of correctly classified instances out of the total instances. Our approach achieved the highest accuracy with the XGBoost classifier at 99.37%, followed by Random Forest at 98.78%. Logistic Regression, Decision Tree, and SVM achieved accuracies of 96.35%, 97.87%, and 96.94% respectively.
2) *AUC (Area Under the Curve):* Denotes the area under the Receiver Operating Characteristic (ROC) curve, which measures the classifier's ability to distinguish between positive and negative instances. XGBoost also outperformed other classifiers in AUC with a value of 0.9989, followed by Random Forest at 0.9978.

3) *TPR (True Positive Rate):* Indicates the proportion of actual positive instances that were correctly identified as positive by the classifier. XGBoost exhibited the highest TPR at 98.83%, followed closely by Random Forest at 98.50%.
4) *FPR (False Positive Rate):* Represents the proportion of actual negative instances that were incorrectly classified as positive by the classifier. Logistic Regression had the lowest FPR at 4.92%, followed by Decision Tree and SVM.
5) *FNR (False Negative Rate):* Denotes the proportion of actual positive instances that were incorrectly classified as negative by the classifier. XGBoost had the lowest FNR at 1.29%, indicating its effectiveness in minimizing false negatives.

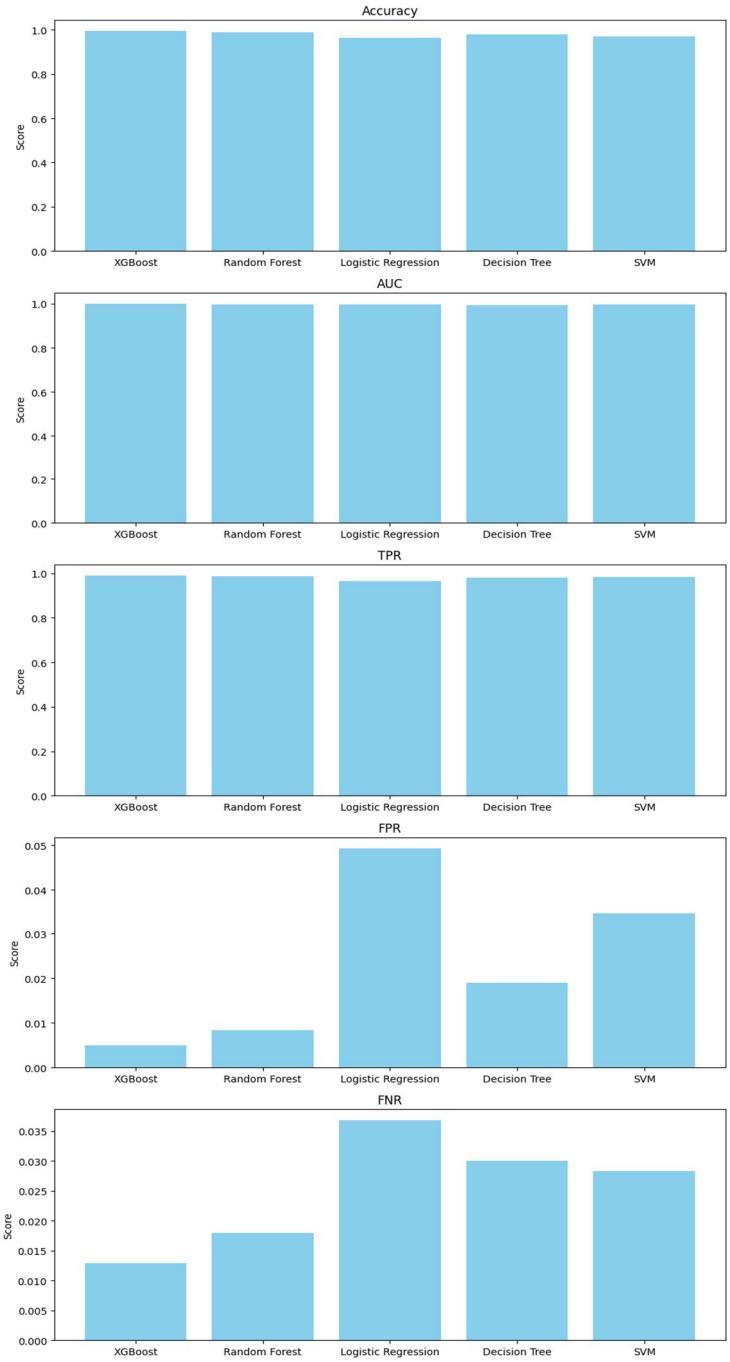

Fig. 3 Performance Comparison of our approach using various classifiers

Overall, the results demonstrate that XGBoost consistently outperforms other classifiers across multiple metrics, including Accuracy, AUC, TPR, FPR, and FNR. However, the choice of classifier may depend on specific requirements and constraints of the application domain.

V. CONCLUSION

This research paper presents a comprehensive analysis of anti-phishing approaches and introduces a novel methodology for effectively detecting phishing websites. Through extensive experimentation and evaluation, the efficacy of the proposed approach is demonstrated across various metrics and compared with existing state-of-the-art techniques. The study involves analyzing and extracting features from both the URL structure and the source code of webpages, utilizing machine learning classifiers to distinguish between legitimate and phishing websites. A range of classifiers including XGBoost, Random Forest, Logistic Regression, Decision Tree, and SVM are explored, with their performance evaluated based on metrics such as accuracy, area under the curve (AUC), true positive rate (TPR), false positive rate (FPR), and false negative rate (FNR). The results indicate that the proposed approach, particularly when coupled with the XGBoost classifier, outperforms existing methods in terms of accuracy, AUC, and TPR. Moreover, the approach exhibits language independence, search-engine independence, third-party independence, and the ability to detect zero-hour attacks, making it a robust solution for combating phishing threats in diverse environments. Overall, this research contributes to ongoing efforts in cybersecurity by providing an effective and efficient means of phishing detection. Future work may involve further refinement of the feature extraction process, exploration of additional machine learning algorithms, and evaluation of the approach on larger and more diverse datasets to enhance its scalability and generalizability. Continuously improving anti-phishing techniques is essential to better protect users from online security threats and safeguard the integrity of digital ecosystems.

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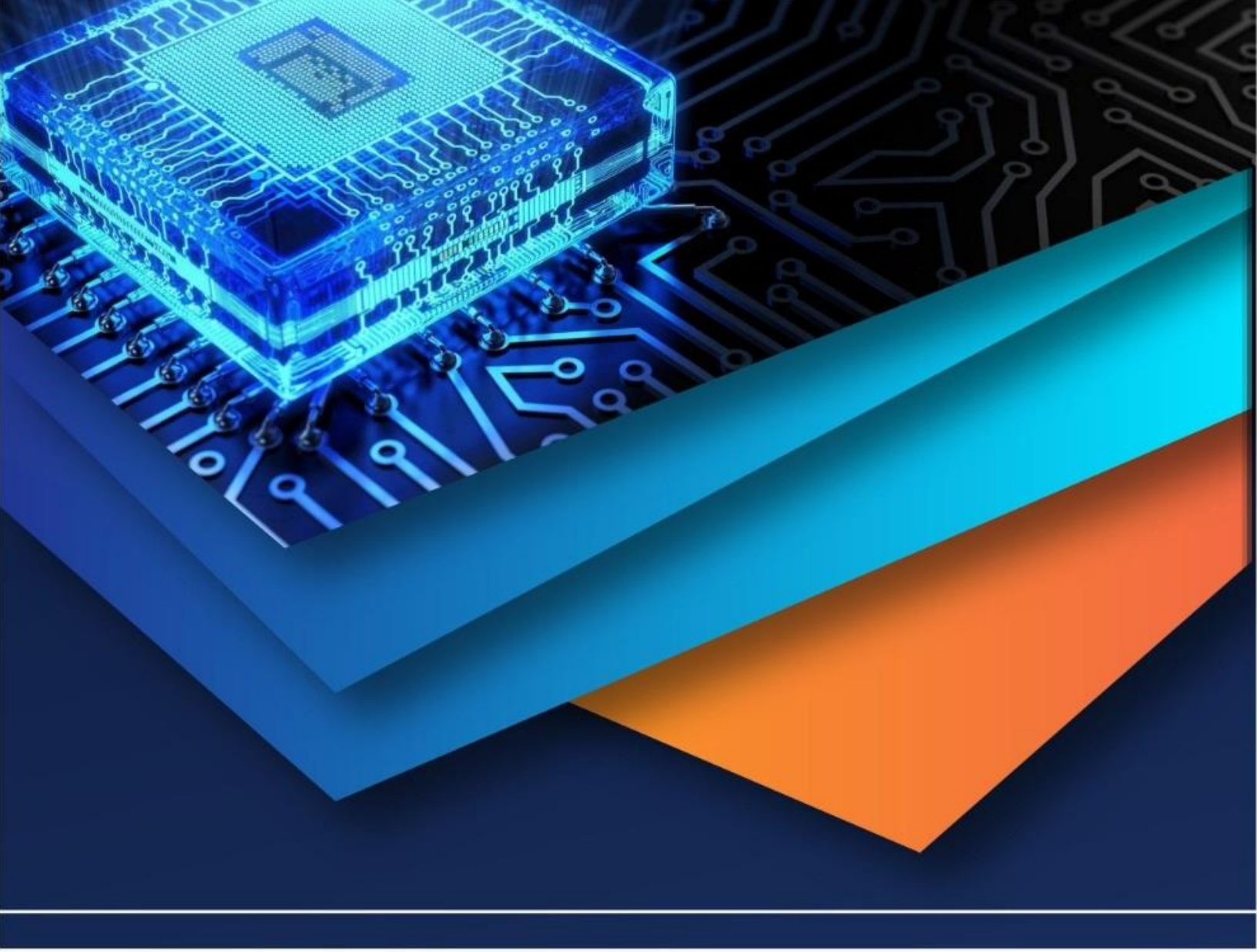

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