AI Based Phishing Detection Techniques: A Comparative Analysis of Model Performance

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Abstract: Phishing attacks continue to pose significant threats to cybersecurity, targeting individuals, businesses, and organizations worldwide. In response, researchers and practitioners have turned to artificial intelligence (AI) techniques to enhance phishing detection capabilities. This paper presents a comparative analysis of AI-based phishing detection techniques, evaluating the performance of various machine learning (ML) and deep learning (DL) models in identifying phishing attempts. The study explores a diverse range of features, including lexical, visual, and behavioral characteristics extracted from phishing emails and websites. The findings contribute to the understanding of the strengths and limitations of AI-based phishing detection approaches, offering insights into the most effective techniques for mitigating phishing threats in various contexts. Additionally, the study identifies areas for future research and development, such as the integration of ensemble learning methods and the incorporation of explainable AI techniques to enhance model interpretability and transparency. Overall, this comparative analysis provides valuable guidance for cybersecurity practitioners and decision-makers in selecting and deploying AI-based phishing detection solutions to bolster their defenses against evolving cyber threats.

Keywords: Phishing detection, artificial intelligence, machine learning, deep learning

Introduction

Phishing attacks remain one of the most pervasive and damaging cyber threats in the digital age, with attackers continuously evolving their techniques to deceive unsuspecting victims. These attacks often involve the fraudulent acquisition of sensitive information, such as usernames, passwords, and financial details, by masquerading as trustworthy entities in electronic communications. The escalating sophistication of phishing techniques necessitates the development of advanced detection mechanisms that can preemptively identify and mitigate these threats. Consequently, artificial intelligence (AI) has emerged as a promising avenue for enhancing

the efficacy of phishing detection systems. The utilization of AI in phishing detection capitalizes on the capability of machine learning (ML) and deep learning (DL) algorithms to discern patterns and anomalies within vast datasets. Unlike traditional rule-based systems that rely on predefined heuristics, AI-based methods can learn from data, adapt to new threats, and improve over time. This adaptability is crucial in the constantly shifting landscape of cyber threats, where attackers frequently modify their tactics to evade detection. The integration of AI into phishing detection not only augments the accuracy of identifying malicious activities but also reduces the reliance on human intervention, thereby enabling real-time threat response and mitigation.

In this study, we undertake a comprehensive analysis of various AI-based phishing detection techniques, focusing on their performance metrics and robustness against sophisticated attack vectors. The analysis encompasses a range of ML and DL models, including support vector machines (SVM), random forests, convolutional neural networks (CNN), and recurrent neural networks (RNN). By leveraging a diverse dataset that includes lexical, visual, and behavioral features extracted from phishing emails and websites, we aim to provide a holistic evaluation of these models. The dataset used in this study is compiled from multiple sources, ensuring a broad representation of phishing instances and enhancing the generalizability of our findings.

Literature Review

The application of machine learning (ML) and deep learning (DL) in phishing detection has gained considerable attention in recent years, driven by the need for more adaptive and robust cybersecurity measures. Early studies, such as those by Fette et al. (2007), utilized simple ML techniques like Naive Bayes classifiers to detect phishing emails based on textual features. These initial efforts demonstrated the potential of ML in improving detection accuracy but were limited by the models' reliance on predefined features and their susceptibility to evolving phishing tactics. Subsequent research by Bergholz et al. (2010) advanced this work by integrating more sophisticated feature extraction methods and ensemble learning techniques, resulting in higher detection rates. However, these approaches still struggled with high false positive rates and the inability to generalize across different types of phishing attacks.

In recent years, deep learning has emerged as a powerful tool for phishing detection due to its ability to automatically extract relevant features from raw data. Rao and Pais (2019) explored the use of Convolutional Neural Networks (CNNs) for detecting phishing websites by analyzing their visual similarity to legitimate sites. Their study reported a significant improvement in detection accuracy, achieving an F1-score of 0.93, which outperformed traditional ML models. Similarly, Bahnsen et al. (2018) employed Recurrent Neural Networks (RNNs) to analyze the sequential nature of phishing emails, demonstrating the effectiveness of DL in capturing temporal dependencies that are often indicative of phishing attempts. Despite these advancements, deep learning models are computationally intensive and require large datasets for training, which can be a barrier to their widespread adoption in resource-constrained environments.

Methodology

This study aims to evaluate the efficacy of various AI-based models in detecting phishing attacks by conducting a comparative analysis. The methodology involves several key stages, including data collection, feature extraction, model selection, training and evaluation, robustness testing, and interpretability analysis. Each stage is meticulously designed to ensure the reliability and validity of the findings.

Data Collection

A comprehensive dataset comprising phishing and legitimate emails and websites was compiled from multiple sources, including publicly available phishing repositories, such as PhishTank, and email datasets from organizations. The dataset was balanced to include an equal number of phishing and legitimate samples, ensuring that the models were not biased towards either class. In total, the dataset consisted of 50,000 samples, with 25,000 phishing instances and 25,000 legitimate instances. The data was preprocessed to remove duplicates, irrelevant information, and to normalize the features for subsequent analysis.

Feature Extraction

Feature extraction is a critical step in the phishing detection process. For this study, a hybrid feature extraction approach was adopted, incorporating lexical, visual, and behavioral features. Lexical features include the analysis of URLs, domain names, and email text, utilizing techniques such as

term frequency-inverse document frequency (TF-IDF) and bag-of-words. Visual features were extracted using image processing techniques to analyze the visual similarity between phishing websites and legitimate ones, leveraging convolutional neural networks (CNNs). Behavioral features involved tracking user interactions with emails and websites, such as click patterns and time spent on a page, captured through session logs and analyzed using recurrent neural networks (RNNs).

Model Selection and Training

The study evaluated a variety of machine learning and deep learning models, including Support Vector Machines (SVM), Random Forests, Logistic Regression, Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks. These models were selected based on their proven efficacy in previous cybersecurity research. The dataset was divided into training (70%), validation (15%), and test (15%) sets. Hyperparameter tuning was performed using grid search and cross-validation techniques to optimize the model parameters. The training process was conducted on a high-performance computing cluster to handle the computational demands of deep learning models.

Results

The results from Table 1 indicate that deep learning models, particularly LSTM networks, significantly outperform traditional machine learning models in terms of accuracy, precision, recall, F1-score, and AUC-ROC. The LSTM model achieved the highest accuracy of 96.7%, demonstrating its superior capability in capturing long-term dependencies in the data, which is crucial for effective phishing detection. The CNN model also performed exceptionally well, with an accuracy of 96.0%, highlighting its strength in visual feature extraction from phishing websites.

When evaluating robustness against adversarial attacks (Table 2), deep learning models again showed resilience, with the LSTM and CNN models maintaining high accuracy and F1-scores even under adversarial conditions. The LSTM model's accuracy only dropped to 94.0%, and the CNN model's to 92.5%, compared to more significant drops observed in traditional models like SVM and Logistic Regression. This suggests that deep learning models not only excel in standard

phishing detection but also offer better defenses against sophisticated evasion tactics employed by attackers.

The explainability of these models, enhanced through techniques such as SHAP and LIME, provided insights into the decision-making processes. For instance, lexical features such as URL structure and domain age were critical in identifying phishing attempts in traditional models. In contrast, deep learning models utilized a combination of lexical, visual, and behavioral features, with CNNs focusing on visual similarities and LSTMs analyzing sequential patterns in user interactions.

The integration of XAI techniques ensured that the AI-driven phishing detection systems were not black boxes, thereby increasing their trustworthiness and facilitating their deployment in real-world scenarios. The transparency offered by these explainable models helps cybersecurity professionals understand and improve the detection mechanisms continually.

Discussion

The results of our study underscore the significant advancements AI and machine learning bring to cybersecurity, specifically in phishing detection. The comparative analysis revealed that deep learning models, particularly LSTM and CNN, offer superior performance across various metrics, including accuracy, precision, recall, F1-score, and AUC-ROC.

Implications of Findings

The LSTM model's exceptional performance can be attributed to its ability to capture temporal dependencies and patterns in data, making it highly effective for sequential data analysis inherent in phishing detection. CNNs also demonstrated strong performance due to their capability to extract hierarchical features from input data, which is beneficial in identifying complex patterns associated with phishing URLs.

Traditional models like SVM and Logistic Regression, while still useful, showed lower performance compared to deep learning models. This suggests that as phishing tactics evolve, more sophisticated models that can learn intricate patterns and relationships in data are required.

Adversarial Robustness

The study also highlights the importance of adversarial robustness in phishing detection models. Deep learning models like LSTM and CNN showed higher resilience against adversarial attacks, maintaining their performance even under challenging conditions. This is critical for real-world applications where attackers continuously adapt their strategies to evade detection.

Practical Applications

The findings of this study have practical implications for organizations looking to enhance their cybersecurity measures. Implementing LSTM-based detection systems can significantly improve the accuracy and reliability of phishing detection, reducing the risk of successful phishing attacks. Additionally, the robustness of these models against adversarial attacks ensures sustained protection even as threat tactics evolve.

Conclusion

In this study, we explored AI-based phishing detection techniques, focusing on the comparative analysis of model performance, adversarial robustness, and practical implications. The findings highlight the efficacy of deep learning models, particularly LSTM and CNN, in detecting phishing attacks with high accuracy and resilience against adversarial manipulations. Our results consistently demonstrate that LSTM and CNN models outperform traditional machine learning algorithms such as SVM and Logistic Regression across multiple datasets. The superior performance of deep learning models can be attributed to their ability to capture intricate patterns and temporal dependencies in phishing data, thereby enhancing detection accuracy and reducing false positives.

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