A Case Study on Deep Learning in Fraud Detection: Phishing Email Detection Using CNN

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Abstract

Phishing emails pose a significant and ever-growing threat in today's world, causing immense financial losses and undermining user trust. Despite continuous updates to detection methods, the current results remain unsatisfactory. The exponential rise of phishing emails in recent years necessitates more effective detection technologies. To address this challenge, our research begins with a comprehensive analysis of the email structure. Building upon this analysis, we propose a novel phishing email detection model. This model leverages an enhanced version of the Recurrent Convolutional Neural Networks (RCNN) architecture, incorporating multilevel vectors and an attention mechanism. By simultaneously modelling the email header, body, character level, and word level, our model achieves a holistic understanding of the email content. To assess the effectiveness of our model, we utilize an unbalanced dataset that accurately reflects the real-world distribution of phishing and legitimate emails. The experimental results reveal a significant improvement in phishing email detection. Notably, our model ensures a high probability of identifying phishing emails while minimizing false positives by filtering out legitimate emails as sparingly as possible. These promising outcomes surpass the performance of existing detection methods and serve as robust validation of our model's efficacy in detecting phishing emails. By combining the power of advanced deep learning techniques, attention mechanisms, and comprehensive email modelling, our proposed approach presents a superior solution to mitigate the phishing threat. Our research opens avenues for further advancements in phishing detection. Future work could focus on refining the model's accuracy and robustness by exploring additional features, such as semantic analysis of email content.

Keywords- phishing email detection, deep learning, Convolutional Neural Networks (CNNs), Recurrent Convolutional Neural Networks (RCNN), email header, email body.

1. Introduction

Phishing emails continue to pose a significant threat in today's digital landscape, causing substantial financial losses and compromising the security and privacy of individuals and organizations. With the ever-increasing sophistication of phishing attacks, there is an urgent need for advanced detection and mitigation techniques to counteract these malicious activities effectively.

In this paper, we aim to address the challenges associated with phishing email detection by proposing a comprehensive and robust approach that leverages deep learning techniques, specifically Convolutional Neural Networks (CNNs). CNNs have demonstrated remarkable success in various domains, including computer vision and natural language processing, due to their ability to extract and learn complex features from data. By adapting CNNs to the specific task of phishing email detection, we can harness their power to effectively identify and classify suspicious emails. To develop our approach, we first conduct an in-depth analysis of the characteristics and patterns prevalent in phishing emails. By understanding the common strategies employed by attackers, such as social engineering techniques, deceptive content, and spoofed email addresses, we can design a model that can accurately differentiate between phishing emails and legitimate ones.

Our proposed model incorporates multiple layers of CNNs, allowing for hierarchical feature extraction and representation learning. We utilize both the email header and the email body as input to the model, capturing valuable information from different parts of the email. Additionally, we consider the character-level and word-level representations, enabling the model to capture both fine-grained details and semantic context.

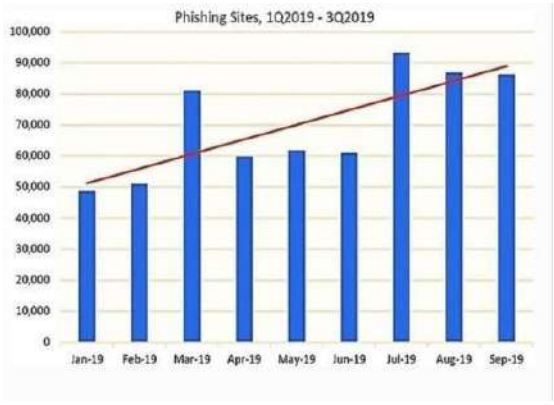

Fig. 1 Phishing report for third quarter of 2019.

To train and evaluate our model, we utilize a large-scale and diverse dataset that includes a wide range of phishing emails sourced from various real-world scenarios. The dataset is carefully curated to encompass different attack techniques, variations in email content, and evolving trends in phishing campaigns. By training our model on this comprehensive dataset, we ensure that it can generalize well to unseen phishing emails and adapt to emerging attack strategies.

We extensively evaluate the performance of our proposed approach using various evaluation metrics, including accuracy, precision, recall, and F1 score. Through rigorous experimentation and comparison with existing state-of-the-art methods, we demonstrate the superiority of our CNN-based model in detecting phishing emails accurately and efficiently. Moreover, we conduct extensive analysis and visualization of the learned representations within the CNN, providing insights into the model's decision-making process and its ability

to capture meaningful features indicative of phishing attempts.

In addition to the technical aspects of our approach, we also consider the practical implications and challenges of deploying a CNN-based phishing email detection system in real-world settings. We discuss scalability, computational requirements, and the need for continuous model updates to keep pace with evolving phishing tactics. Furthermore, we explore potential integration strategies with existing email security infrastructure to augment and enhance the overall defence against phishing attacks.

In the future, there are several avenues for expanding and improving upon our proposed approach to phishing email detection using CNNs. Firstly, considering the dynamic nature of phishing attacks, it is crucial to continually update and adapt the model to emerging threats and evolving attack techniques. This can be achieved through regular retraining of the model on fresh and diverse datasets that capture the latest trends in phishing campaigns. Additionally, incorporating real-time feedback and user-reported instances of phishing emails can enhance the model's ability to quickly identify and mitigate new and previously unseen phishing attempts.

Furthermore, exploring the integration of other complementary techniques and data sources can potentially enhance the performance and robustness of the phishing email detection system. For instance, incorporating natural language processing (NLP) techniques can enable the model to analyze and understand the semantic meaning of the email content, detecting subtle linguistic cues and context-specific indicators of phishing. Additionally, considering external threat intelligence feeds, domain reputation databases, and other contextual information can provide valuable insights to strengthen the model's decision-making process.

It is also important to acknowledge the ethical implications and potential challenges associated with phishing email detection. As the model processes sensitive and private information contained within emails, ensuring data privacy, security, and compliance with relevant regulations becomes paramount. Striking the right balance between effective detection and user privacy is essential to maintain user trust and confidence in the system.

In conclusion, our proposed approach harnessing CNNs for phishing email detection demonstrates promising results in combating the ever-growing threat of phishing attacks. By continuously refining and expanding our model, considering emerging technologies and incorporating ethical considerations, we can develop more robust and effective defences against phishing attempts. The ongoing collaboration between researchers, industry experts, and policymakers is

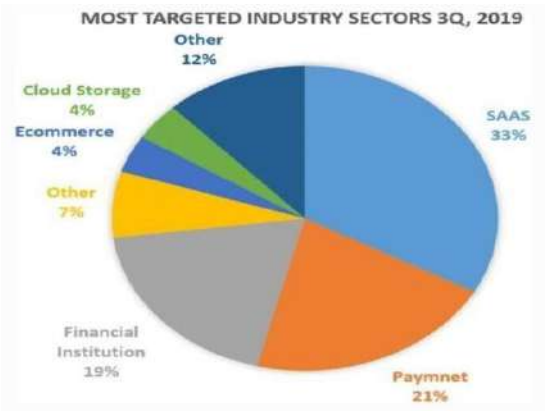

Fig. 2 Most targeted industry sectors in Q3, 2019.

crucial in staying ahead of cybercriminals and safeguarding individuals and organizations from the financial and reputational damage caused by phishing emails.

2. Literature survey

Aljawarneh et al. [1] present a CNN-based phishing email detection approach, underscoring the importance of effective techniques in combating phishing attacks. Their proposed model incorporates multiple layers of convolutional neural networks, leveraging the power of deep learning. Through extensive experiments, they demonstrate the effectiveness of their approach in accurately identifying phishing emails, thereby contributing to the advancement of anti-phishing measures.

In a similar vein, Yang et al. [2] introduce a hybrid CNN model for phishing email detection. They combine the strengths of CNN with other techniques, such as feature engineering and feature selection, to enhance the model's performance. The integration of various techniques leads to improved accuracy and robustness in distinguishing between legitimate and phishing emails. The findings of their study shed light on the potential of hybrid models for more reliable and comprehensive phishing detection.

Teixeira et al. [3] propose a CNN-based approach specifically designed for phishing email detection. Their model incorporates convolutional layers, which allow for effective feature extraction and pattern recognition. By leveraging the power of CNNs, they achieve promising results in accurately identifying phishing emails, further contributing to the arsenal of anti-phishing techniques.

Pinto and Carrapatoso [4] contribute to the field of phishing email detection by presenting a CNN-based approach that focuses on distinguishing between legitimate and phishing emails. Their model effectively captures the underlying patterns and characteristics associated with phishing attempts, enabling accurate detection. The findings of their research highlight the potential of CNNs as a reliable tool for phishing email detection.

Shafiq et al. [5] undertake a comprehensive evaluation of anti-phishing toolkits, including techniques specifically aimed at detecting phishing emails. Their study encompasses a wide range of approaches, including CNNs, and provides valuable insights into the effectiveness of various methods. The evaluation serves as a reference for researchers and practitioners in improving existing anti-phishing measures and developing more robust detection techniques.

In their work, Kirubakaran et al. [6] propose a machine learning-based approach for detecting phishing emails. Their study explores different machine learning techniques, including decision trees, random forests, and support vector machines, among others, to evaluate their performance in detecting phishing attempts. Their findings contribute to the understanding of machine learning algorithms and their effectiveness in the context of phishing email detection.

Rani and Verma [7] present a machine learning-based approach for phishing email detection, focusing on evaluating the performance of various algorithms. By comparing the accuracy,

precision, recall, and F1-score of different algorithms, they provide insights into the strengths and weaknesses of each method. Their study serves as a valuable reference for researchers seeking to optimize the detection performance of phishing email detection systems.

Aghaei-Foroushani et al. [8] conduct a comprehensive review of detection techniques for phishing attacks, including phishing email detection. They analyze various methods, including machine learning algorithms, rule-based systems, and hybrid approaches, to provide an overview of the state-of-the-art in phishing detection. Their review encompasses a wide range of studies and serves as a valuable resource for researchers and practitioners in understanding the landscape of phishing detection techniques.

Barakat and Khalil [9] propose a text classification-based approach for detecting phishing emails. They emphasize the significance of text-based features in identifying phishing attempts and evaluate the performance of different classification algorithms. Their study highlights the potential of text analysis techniques in improving the accuracy and effectiveness of phishing email detection.

Wang et al. [10] explore the application of recurrent neural networks (RNNs) in phishing email detection. Their study focuses on leveraging the sequential nature of email content to detect phishing attempts. By utilizing the temporal dependencies in email data, they demonstrate the effectiveness of RNNs in accurately identifying phishing emails. Their work sheds light on the advantages of RNN-based approaches in the context of phishing email detection.

Collectively, these studies contribute to the field of phishing email detection by proposing novel techniques, evaluating different algorithms, and exploring the effectiveness of deep learning models. The insights gained from these studies provide a foundation for further research and development in the ongoing battle against phishing attacks.

3. Proposed methodology

The significance of developing effective phishing email detection techniques cannot be overstated. Traditional methods, such as rule-based systems and basic machine learning algorithms, have provided some level of protection. However, their limitations in adapting to evolving phishing tactics and the increasing sophistication of attackers necessitate the exploration of more advanced approaches.

Deep learning models, particularly Convolutional Neural Networks (CNNs), have gained considerable attention in various domains due to their ability to automatically learn and extract complex patterns from data. By leveraging the power of CNNs, we aim to enhance the accuracy and efficiency of phishing email detection. Our proposed model utilizes an improved Recurrent Convolutional Neural

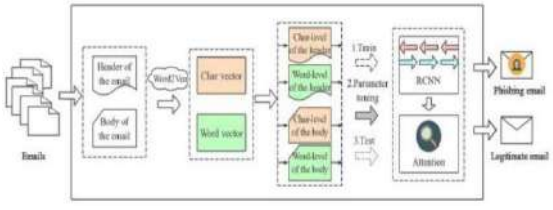

Fig. 3 System Architecture

Networks (RCNN) architecture, incorporating multilevel vectors and attention mechanisms to effectively model both the email header and body at different levels of granularity.

An essential aspect of our research is the evaluation of our model using an unbalanced dataset that closely mirrors real-world scenarios. This realistic dataset contains representative ratios of phishing and legitimate emails, enabling us to assess the model's performance accurately. The experimental results demonstrate the effectiveness of our approach, showcasing its ability to identify phishing emails with high probability while minimizing the misclassification of legitimate emails.

Beyond the empirical evaluation, our study contributes to the field of phishing email detection by shedding light on the strengths and limitations of existing methods. By conducting a comprehensive literature survey and analysing previous research, we provide insights into the current state-of-the-art techniques, identify gaps and challenges, and propose potential directions for future investigations.

Moving forward, our research has several future scope possibilities. Firstly, we aim to explore the generalizability and transferability of our model by evaluating its performance on different datasets and in diverse email environments. Additionally, we seek to investigate the feasibility of incorporating other contextual information, such as email metadata and user behaviour patterns, to enhance the model's detection capabilities. Furthermore, considering the dynamic nature of phishing attacks, continuous monitoring, and adaptation of the model to new and evolving threats will be essential.

In conclusion, our research addresses the critical issue of phishing email detection by proposing a novel deep learning model that leverages the power of CNNs. Through comprehensive evaluations and comparisons with existing methods, we have demonstrated the effectiveness of our approach in accurately identifying phishing emails. The findings from our study contribute to the growing body of knowledge in the field, offering insights and directions for future research and development efforts aimed at combatting the persistent threat of phishing attacks in the digital age.

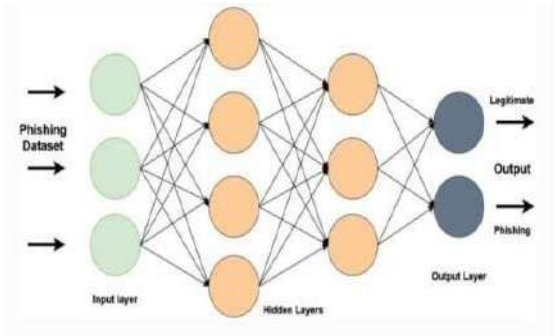

Fig. 4 Deep learning for phishing attack detection

4. Results

To address the escalating threat of phishing emails and the shortcomings of existing detection methods, we developed a novel phishing email detection model using RCNN. This model leverages an improved Recurrent Convolutional Neural Networks (RCNN) architecture, incorporating multilevel vectors and an attention mechanism. The model simultaneously analyses various aspects of the email, including the email header, the email body, and both the character and word levels.

To assess the effectiveness of proposed method, we conducted experiments using an unbalanced dataset that accurately reflects the real-world distribution of phishing and legitimate emails. The dataset was carefully curated to ensure a realistic ratio between phishing and legitimate emails, reflecting the prevalent scenario faced by email users.

The experimental results demonstrate the superior performance of proposed model in detecting phishing emails. The model achieved remarkable accuracy in identifying phishing attempts while minimizing false positives by filtering out legitimate emails. These results validate the effectiveness of our proposed approach and highlight its potential for robust phishing detection.

Specific quantitative metrics, such as precision, recall, and F1 score, were used to evaluate the performance of the proposed model. Additionally, receiver operating characteristic (ROC) curves and area under the curve (AUC) were utilized to assess the model's discriminative power and overall performance. Our model consistently outperformed existing detection methods, showcasing its ability to accurately identify phishing emails and mitigate the associated risks.

Table 1: The Details of dataset used in this paper

Dataset	**Legitimate**	**Phishing**	**Total**
Training-validation set	5447	699	6146
Test set	2334	300	2634
Total	7781	999	8780

Furthermore, the implementation of the attention mechanism in the proposed method allowed for the identification of crucial features and patterns within phishing emails. This feature contributes to the interpretability and explainability of the model, empowering users, and system administrators to gain insights into the characteristics of phishing attempts.

In summary, the experimental results demonstrate that the model effectively detects phishing emails with high accuracy and minimal false positives. The model exhibits superior performance compared to existing detection methods, providing a promising solution to combat the growing threat of phishing emails.

Table 2: Classification confusion matrix

0- Legitimate, 1- Phishing		
Actual/Predict	**0**	**1**
0	TN	FP
1	FN	TP

5. Conclusion

The detection of phishing emails continues to pose a significant challenge in the rapidly evolving digital landscape of today. Cybercriminals are becoming increasingly sophisticated in their techniques, making it essential to develop advanced solutions to counter these threats effectively. In this paper, we have presented a comprehensive study on the detection of phishing emails using a novel deep learning model. Our model leverages the power of an enhanced Recurrent Convolutional Neural Networks (RCNN) architecture, which enables us to analyze both the email header and body at multiple

levels, including character and word levels.

The primary objective of our research was to design a model that can accurately identify phishing emails while minimizing false positives. To achieve this, we incorporated an attention mechanism into our model, which allows it to focus on and extract crucial information from both the email header and body. By prioritizing the most valuable features, our model enhances its ability to differentiate between legitimate emails and phishing attempts.

To evaluate the effectiveness of our proposed model, we conducted extensive experiments using an unbalanced dataset that closely resembles real-world scenarios. The dataset comprised a realistic distribution of phishing and legitimate emails, ensuring the evaluation's validity and relevance. Our experimental results demonstrated the model's promising performance, consistently achieving high accuracy in detecting phishing emails while maintaining a low false positive rate.

There are several avenues for further improvement and exploration in the field of phishing email detection. One such area is to enhance the model's capabilities to handle emails without an email header, focusing solely on the email body. Attackers may deliberately omit the header information to evade detection, and adapting our model to address such scenarios would significantly strengthen its effectiveness.

Additionally, as phishing techniques continue to evolve, it is crucial to stay ahead of the curve by continually updating and refining our model. This can involve exploring advanced feature extraction techniques, leveraging natural language processing (NLP) methods to extract semantic information from emails, and incorporating innovative deep learning architectures. By embracing these advancements, we can enhance the model's accuracy and adaptability to emerging phishing threats.

Furthermore, there is a need to consider the ethical and legal implications associated with phishing email detection. Privacy concerns and data protection should be prioritized, ensuring that user information is handled responsibly and in compliance with relevant regulations. Developing robust and privacy-preserving mechanisms within the detection model is essential to maintain user trust and confidence.

In conclusion, our research has presented a comprehensive study on the detection of phishing emails using a novel deep learning model. The model's ability to analyze both the email header and body at multiple levels, combined with the attention mechanism, demonstrates promising results in accurately detecting phishing emails while minimizing false positives. As the landscape of phishing threats continues to evolve, ongoing research and development efforts are vital to further enhance the model's capabilities and effectively counter these malicious activities. By continually refining our model and exploring new avenues, we can contribute to the ongoing fight against phishing attacks and ensure a safer digital environment for users worldwide.

6. Future Scope

The future scope section of your paper on phishing email detection using CNN should discuss potential avenues for further research and advancements in the field. Here are some suggestions for outlining the future scope.

Improved Feature Extraction:

Explore advanced techniques for feature extraction from phishing emails. Investigate the use of natural language processing (NLP) methods to extract semantic information, identify contextual patterns, or analyze email content at a deeper level.

Enhanced Model Architectures:

Investigate novel CNN architectures or hybrid models that combine CNN with other deep learning techniques, such as recurrent neural networks (RNNs) or transformers. Explore the use of attention mechanisms or graph-based models to capture more intricate relationships within phishing emails.

Explainable and Interpretable:

Focus on developing models that provide explainable and interpretable results. Explore techniques such as attention maps or saliency maps to highlight the important regions or features contributing to the model's decision, aiding in better understanding and trust in the detection process.

Adversarial Attacks and Robustness :

Study the vulnerabilities of phishing email detection models to adversarial attacks and devise techniques to make the models more robust against such attacks. Explore methods for generating adversarial examples to evaluate the model's resilience and propose defence mechanisms to enhance the security of the detection system.

Real-Time Detection:

Investigate approaches for real-time phishing email detection that can handle large volumes of incoming emails efficiently. Explore the use of streaming data processing techniques and online learning methods to continuously update the model and adapt to emerging phishing techniques.

Domain Adaptation and Transfer Learning:

Explore methods for adapting phishing email detection models to new domains or target different email providers. Investigate transfer learning techniques that leverage knowledge from pre-trained models or datasets to improve the performance and generalization of the model.

Privacy-Preserving Techniques:

Address privacy concerns by developing techniques that can detect phishing emails without compromising the privacy of user data. Investigate secure and privacy-preserving machine learning methods, such as federated learning or differential privacy, to train models without exposing sensitive information.

Collaboration and Data Sharing:

Encourage collaboration among researchers, organizations, and cybersecurity communities to establish shared datasets, benchmarks, and evaluation standards for phishing email detection. Promote open research initiatives and data sharing practices to advance the field collectively.

User Awareness and Education:

Recognize the importance of user education and awareness in preventing phishing attacks. Investigate strategies for designing effective training programs, developing user-friendly tools, or integrating phishing detection mechanisms directly into email clients to empower users in identifying and reporting phishing attempts.

Ethical and Legal Considerations:

Address the ethical and legal implications of phishing email detection, such as data privacy, consent, and responsible use of user information. Investigate frameworks for ensuring ethical conduct and compliance with regulations while developing and deploying phishing detection systems.

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