Evaluating Large Language Models for Phishing Detection, Self-Consistency, Faithfulness, and Explainability

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Abstract-Phishing attacks remain one of the most prevalent and persistent cybersecurity threat with attackers continuously evolving and intensifying tactics to evade the general detection system. Despite significant advances in artificial intelligence and machine learning, faithfully reproducing the interpretable reasoning with classification and explainability that underpin phishing judgments remains challenging. Due to recent advancement in Natural Language Processing, Large Language Models (LLMs) show a promising direction and potential for improving domain specific phishing classification tasks. However, enhancing the reliability and robustness of classification models requires not only accurate predictions from LLMs but also consistent and trustworthy explanations aligning with those predictions. Therefore, a key question remains: Can LLMs not only classify phishing emails accurately but also generate explanations that are reliably aligned with their predictions and internally selfconsistent? To answer these questions, we have fine-tuned transformer-based models, including BERT, Llama models, and Wizard, to improve domain relevance and make them more tailored to phishing specific distinctions, using Binary Sequence Classification, Contrastive Learning (CL) and Direct Preference Optimization (DPO). To that end, we examined their performance in phishing classification and explainability by applying the ConsistenCy measure based on SHAPley values (CC-SHAP), which measures prediction-explanation token alignment to test the model's internal faithfulness and consistency and uncover the rationale behind its predictions and reasoning. Overall, our findings show that Llama models exhibit stronger prediction-explanation token alignment with higher CC-SHAP scores despite lacking reliable decision-making accuracy, whereas Wizard achieves better prediction accuracy but lower CC-SHAP scores. The code in available in the GitHub repository¹.

Index Terms—Phishing, Large Language Models, Fine Tuning, Human-like Models, Consistency, Faithfulness

1. Introduction

Phishing attacks are malicious activities where attackers try to impersonate themselves as a trustworthy source to get sensitive information from certain targeted users [1]. Despite the massive technological shift over cybersecurity over several years, many organizations, individuals, and even security experts are becoming victims of phishing emails. It has been reported by the Anti-Phishing Working Group (APWG) that the number of phishing emails exponentially grew from **44,008 in first quarter of 2020 to 128,926 by the end of the year** [2]. The techniques such as rule-based detection, email filters and blacklisting of malicious domains served as a traditional anti-phishing measures. However, the dynamic tactics of attackers like obfuscation, impersonation, and personalized social engineering methodologies bypassed the conventional strategies for defense [3],highlighting the need for more advanced and sophisticated detection methods.

To address this challenge, initially, scholars were focused towards Machine Learning methods with complex and variety of dataset to comprehend the complex patterns within emails which is often considered as indicative measures in phishing attempt and detection [4]. These models utilize the mathematical principles of weighted feature analysis to make predictions. However, despite their effectiveness in many cases in various domain, they often struggle to generalize across evolving attack strategies, lack of interpretability and failing to capture the nuanced reasoning behind the deceptive tactics commonly seen in phishing domain.

With the advancement of Large Language Models LLMs, researchers have redirected their studies towards innovative approaches in phishing detection [5] and analysis. The usage of LLMs includes developing detection systems [6] [7] [8], creating LLM-generated emails to assess the resilience of current phishing detection tools [9] [10] and conducting experimental studies to determine human susceptibility to LLM-crafted phishing emails [11]. Additionally, LLMs are used in explainable AI (XAI) to translate technical outputs into natural language explanations, as in EXPLICATE [12], enhancing user understanding and trust in phishing detection systems. Likewise, a fine-tuned models were used for phishing detection, where explainability was achieved through LIME and Transformer Interpret techniques [13]. Even though they demonstrated the effectiveness of integrating explainability into phishing detection, they primarily rely on post-hoc methods where predictions are first generated by an ML model and then interpreted separately.

However, this area of research is still fundamentally under-explored and limited. In this research study, we aim to systematically investigate different potential of LLMs in phishing detection to explore its capabilities in

^{1.} https://github.com/PsyberSecLab/Fine-Tuning-and-Explainability-for-Phishing-Detection

classification, explanability, and self-consistency to bridge the gap and develop a nuanced understanding of LLMs' potential in cybersecurity. To achieve this goal from this research study, we want to address the following interconnected research questions: 1) How accurate LLMs are while performing phishing classification tasks?, The mere accuracy of these models may not be enough to make LLM models reliable and faithful, thus, we explore the next question i.e. 2) Can LLMs provide internally consistent and contextually grounded explanations that align with their predictions ?

2. Dataset description

We collected the experimental dataset for this research from various sources, as obtaining high-quality datasets for phishing detection is a challenging task itself. Out of three datasets, the Enron Email Corpus, a realworld dataset comprising of 500,000 emails gathered from 158 employees of the Enron corporation, was the primary source for our ham email dataset [14]. Similarly, we used the Nazario dataset for phishing emails [15], which comprised of phishing emails collected between 2004 to 2020 [16]. We used the phishing emails from 2015-2024 as we were only focused on certain attributes of an email such as newer phishing tactics and strategies that have evolved over recent years. As the Nazario dataset collects a large number of phishing emails over a considerable period of time, it is highly respected and often used in phishing-related research. These two datasets were used to fine-tune our various LLMs for phishing detection, and a subset of the same data was also utilized to evaluate the CC-SHAP method.

Source	Email Type	Count
Nazario [15]	Phishing	2500
Enron [14]	Ham	2500
TABLE 1. D	ATASET DESCR	IPTION

In order to ensure cleanliness, consistency, and suitability, the dataset we obtained underwent intensive data pre-processing steps before actual training. The following are the pre-processing steps that we applied on the dataset:

2.1. Data Cleaning

We removed the HTML tags, special symbols, emails that were in different languages, decoded ASCII codes, and unnecessary characters. We used the BeautifulSoup library to parse the HTML email content to remove noise and concentrate on extracting the necessary text from the email.

2.2. Duplicate Removal Balanced Dataset

To avoid over-representation and maintain the dataset's diversity, redundant entries were identified and removed. To balance the dataset and to ensure the model does not bias towards any class of emails, we took the same number of email counts (2500) from both Nazario :phishing and Enron :ham for fine-tuning purposes.

2.3. Feature Extraction

Among multiple attributes and characteristics of an email present in dataset, we were interested in certain attributes of an email such as: **Body**, **Sender**, **Subject** and **Label**. Here, our objective was to find the nuanced semantic and contextual patterns in these extracted features to distinguish between two types of emails that eventually served as a distinct purpose in fine-tuning and evaluation tasks.

3. Methodology

Transformer architecture-based LLMs are outstanding at understanding complex linguistic patterns and relationships, as well as text generation, as they are pre-trained on massive corpora. These abilities help them achieve the state-of-the-art performance in various Natural Language Processing tasks such as text classification, text summarization, language translation, sentiment analysis and so on. Even though these models are proficient at a wide range of Natural Language Processing tasks, their performance as well as effectiveness in domain-specific areas like cybersecurity remain a challenge with resourceintensive training and domain-specific datasets. To resolve the issues, one efficient approach is to leverage knowledge by fine tuning LLMs with high-quality domain-related data while minimizing the need of extensive pre-training on a huge number of parameters [17].

Rather than starting from scratch, fine-tuning uses the existing knowledge base of that particular pre-trained LLM that it learned while training. During the finetuning process, it updates only the required parameters to adjust and fit to certain specific requirements of the tasks [18]. With this underlying principle, we fine-tuned different LLM models with our cyber domain-specific dataset for binary email classification. The main purpose was to get more contextualized embeddings vectors that can effectively differentiate between two classes of emails: phishing and ham. Considering the resources required, we employed Parameter Efficient Fine-Tuning (PEFT) techniques [19] such as Low-Rank Adaptation (LoRA) which simply updates the small set of parameters without requiring to update all the parameters in pre-trained model.

We implemented LoRA [20] based fine-tuning of LLMs. The fundamental idea behind LoRA is to freeze the weights of the original model while adding a small subset of trainable sub-modules to train with additional network layers in transformer architecture. [17] found that fine-tuning only the query and value matrices, rather than all four attention matrices, achieves comparable performance. By keeping only query and value as target modules for LoRA, we fine-tuned our three different large language models: Llama-2-7B, Llama-3-8B, Wizard-7B. Additionally, we also included BERT model for fine tuning with general architecture as it is smaller model compared to other models.

4. Experiments

4.1. Models

In this research study, we used various language models to test different aspects of phishing email detection, including **BERT: bert-base-uncased**, **Llama 7B: meta-llama/Llama-2-7b-hf**, **Llama 8B: llama/Llama-3-8B** and **Wizard 7B: dreamgen/WizardLM-2-7B**. These models were trained on different approaches of fine-tuning to detect phishing and legitimate emails based on the features.

Bidirectional Encoder Representations from Transformers (BERT) [21] was first introduced by Google AI in 2018, which is a ground breaking NLP model known for its bidirectional understanding of text using Masked Language Modeling (MLM) and Next Sentence Prediction (NSP). The reason for choosing BERT for this study, is for its established capabilities in capturing the nuanced relationship between words and sentences in an emails [22]. Llama 7B [23] and Llama 8B [24] are both opensource language models developed by Meta AI and released in 2023 and 2024 respectively. These transformer based models from Meta AI, were leveraged for their ability to process long sequences and their pre-training on large corpora, which is required for effective understanding of phishing strategies. Wizard 7B [25], as fine tuned derivative of foundational LLM Mistral, was chosen for its strong instruction-following abilities and advanced attention mechanism with evol-instruct tuning allowing it to capture phishing characteristics precisely.

4.2. Fine-Tuning Approach

We have employed three major approaches for fine tuning: **Binary Sequence Classification**, **Direct Preference Optimization**, and **Contrastive Learning** using different pre-trained large language models as explained in above section.

4.2.1. Binary Sequence Classification. As one of our fine-tuning approach, we employed general binary sequence classification for phishing detection treats each email as a sequence of tokens, often combining sender, subject, and body and uses a pretrained LLMs models to produce contextualized embeddings for accurate decision. During training, the model minimizes cross-entropy loss on labeled examples. With the fine-tuning on a curated dataset of phishing and ham emails, the model learns to recognize textual patterns, explicit features and semantic cues that distinguish phishing and legitimate emails.

4.2.2. Direct Preference Optimization. During the finetuning process, we used the Nazario and Enron dataset to train our LLM models to differentiate phishing emails from the legitimate. We employed Direct Preference Optimization (DPO), a stable and computationally efficient fine-tuning method that eliminates the need for reward model fitting or extensive hyper-parameter tuning [26]. Rather than relying on explicit labels, our models aimed to learn from the structured email comparisons, analyzing key features such as sender, subject, and body to detect phishing patterns. DPO learns by minimizing the loss, while encouraging models to prefer email structures that align with phishing or legitimate characteristics to replicate its decision-making processes with human-like preferences.

4.2.3. Contrastive Learning. We also employed Contrastive Learning approach to fine-tune the pre-trained language model for the task of phishing email detection. In Contrastive Learning based fine tuning [27], models learn by comparing emails in structured triplets, where one email serves as a reference, another is similar in intent, and the third is the one with dissimilar intent. The email input includes the key features of an email like sender, subject and the body. In the process of training, the model distills its understanding by pulling similar emails closer in its learned representation. While the models push different ones apart, creating a subtle distinguished detection scenario for phishing emails.

5. Explainability and Self-Consistency of LLMs

The explainability is crucial in phishing classification to ensure that model predictions and explanations are transparent and replicate with human-like reasoning. Quantifying natural language explanations is challenging and an emerging research area. We employ the concept of **Consistency Measured based on SHAPley Values (CC-SHAP)** derived from the prior research [28], and adapt it for phishing classification. In our implementation, to quantify how well the model's prediction aligns with its core reasoning and decision-making processes, we extended the original CC-SHAP methodology by computing the SHAP values from the input email text for both the classification and explanation.

The classification SHAP values measure how much each token in the email contributes to that particular decision- PHISHING or LEGITIMATE by evaluating probability shift when individual tokens are masked. To compute SHAP values, we used a perturbation-based masking strategy that selectively replaces tokens with the padding token and evaluates the probability shift in classification outcomes. Specifically, for each token j equation (1) in the input, its contribution is approximated using Monte Carlo sampling as:

$$\phi_j = \frac{1}{N} \sum_{s \in S_j} \left(P(s \cup \{j\}) - P(s) \right)$$
(1)

where:

- N is the total number of Monte Carlo samples,
- S_j is the set of sampled token coalitions that do *not* include token j,
- P(s∪{j}) denotes the model's output probability when token j is unmasked together with the tokens in coalition s,
- P(s) denotes the model's output probability when only the tokens in coalition s are visible (all other tokens, including j, are masked).

During implementation, we randomly select coalitions of tokens, create masked inputs preserving only those coalition tokens, compute each token's marginal contribution as the difference between the model's output probability when token j is included in the coalition and the model's output probability when only the coalition tokens are present. Then, accumulate these contributions across all samples. These SHAP values are normalized by computing a contribution ratio for each token as:

$$c_j = \frac{\phi_j}{\sum_i |\phi_i|} \tag{2}$$

which scales the contributions to values within the range of -1 to 1. The shap values are obtained for both the prediction and the explanation. Subsequently, the cc-shap score is obtained by computing the cosine distance between normalized SHAP vectors for both prediction and explanation, ensuring both vectors are of equal length by re-normalizing them with L1 norm.

$$\text{CC-SHAP} = 1 - \text{cosine-dist}(\phi_{\text{norm}}^{(p)}, \phi_{\text{norm}}^{(e)})$$
(3)

6. Results

6.1. Accuracy of LLM Models in Predicting Ground Truth in Phishing Datasets

We evaluated different LLM models with our combined dataset (Nazario and Enron) and compared the models performance using three types of fine-tuning approaches such as: binary classification, contrastive learning and direct preference optimization. It is observed from Table 2 that binary classification based fine -tuning yielded the good performance across all the models, with BERT achieving 98.89 training accuracy and 98.55 validation accuracy. The results revealed that Llama 7B and Llama 8B also showed strong performance in binary classification with validation accuracies of 90.90 and 93.30 respectively. However, Wizard 7B consistently underperformed, with 83.68 validation accuracy with higher loss of 0.98. This results suggest that Wizard 7B has the weaker generalization compared to other models.

Additionally, with an intention of learning more nuanced semantics involved in the phishing detection which can be reflected in the embeddings, we employed the contrastive based learning. This approach allowed our models to develop more refined contextual representations by comparing positive and negative examples rather than simply predicting the class labels. With this, resulting in embeddings that better reflect the semantic nuances that differentiate the legitimate emails from deceptive signal as phishing emails. The results from Table 3 showed us BERT again has the lowest training and validation losses: 0.003 and 0.007 respectively. Similarly, the Llama 7B and Llama 8B performed comparably low under contrastive learning with training losses of 0.101 and 0.090 and validation losses of 0.137 and 0.088, respectively. Wizard 7B, in contrast to the LLaMA models, exhibited a training loss of 0.451 and a validation loss of 0.463, suggesting that its embeddings may be less reflective and effective in clustering phishing and legitimate emails.

The Direct Preference Optimization (DPO) learns a preference ordering between responses by encouraging the model to assign higher probabilities to preferred responses

and lower probabilities to rejected responses [26]. Likewise, we employed DPO to refine the model's ability to capture the subtle preference differences, while ensuring a enhanced understanding of phishing and ham emails. However,direct preference optimization (DPO) resulted in significantly worse performance across all models, with losses substantially higher than both the binary classification and contrastive learning. We can see from the Table 3 that Llama 7B and Llama 8B both has training losses more than 1.4, suggesting that they struggled to optimize preference-based ranking for phishing classification. Moreover, the Wizard 7B performed the worst beside the types specific models we used with training and validation losses of 10.98 and 11.58 respectively, suggesting this model is not well-suited for this training methodology.

Overall, binary classification results suggests that this is the most effective approach for phishing detection, with BERT outperforming all models in accuracy and loss reduction.

6.2. LLM Model's Explanability, Consistency, and Faithfulness

Building upon our previous findings, where we explored the classification performance and learning capabilities of fine-tuned model, we extended our research to test the explanability, consistency, and faithfulness of these models. To assess model performance, we constructed a dataset consisting of 20 phishing emails from Nazario and 20 legitimate emails from Enron. The results presented in Table 4 highlighted the trade-off between classification accuracy and model's explanation and selfconsistency across different LLM model architectures using the baseline models. Llama 7B and Llama 8B model exhibited high CC-SHAP scores suggesting stronger selfconsistency in their prediction-explanation token alignment with 0.9659 ± 0.030 for phishing, 0.977 ± 0.0169 for ham in Llama 7B and 0.9549 ± 0.052 for phishing and 0.974 ± 0.013 for ham in Llama 8B. However, their phishing accuracy remained low 40 and 30 for Llama 7B and Llama 8B. This suggest that while these models may be consistent in their prediction-explanation token alignment, internal faithfulness, they often struggle to differentiate phishing classification effectively. In contrast, Wizard 7B demonstrated a lower CC-SHAP score for phishing 0.123 ± 0.0906 and ham emails 0.1925 ± 0.123 , yet attained a higher phishing accuracy of 80. This can be implied that Wizard 7B implements the different approach in decision making, and shows lower consistency in their token alignment, prioritizing detection with higher accuracy. Meanwhile, all models performed well in classifying ham emails, with Llama models obtaining 100 accuracy and Wizard 7B 95. This finding suggest that there might be a possible bias towards legitimate emails, potentially introducing the false negatives (False Alarm) in phishing classification.

To gain a better understanding of how different models interpret phishing emails, we applied CC-SHAP explanability and consistency analysis to compare their classification ability and reasoning style across different LLM models using a phishing email as an input as shown in Figure 1. It can be observed that two of these models Llama 8B and Wizard 7B predicted as phishing, while

Model	Training Accuracy (%)	Validation Accuracy (%)	Training Loss	Validation Loss
BERT	98.89	98.55	0.03	0.04
LLaMA 7B	92.15	90.90	0.18	0.19
LLaMA 8B	94.37	93.30	0.15	0.19
Wizard 7B	84.68	83.68	0.87	0.98

TABLE 2. BINARY CLASSIFICATION RESULTS FOR DIFFERENT MODELS AGAINST GROUND TRUTH OF EMAILS

Fine-Tuning Approach	Model	Training Loss	Validation Loss
Contrastive Learning	BERT	0.003	0.007
	LLaMA 7B	0.101	0.137
	LLaMA 8B	0.090	0.088
	Wizard 7B	0.451	0.453
Direct Preference Optimization	BERT	0.063	0.068
	LLaMA 7B	1.493	1.683
	LLaMA 8B	1.405	1.563
	Wizard 7B	10.98	11.58

TABLE 3. CONTRASTIVE LEARNING AND DIRECT PREFERENCE OPTIMIZATION FINE-TUNED RESULTS



We'd like your feedback Your participation will provide valuable information that can help us better serve and protect your online account. Recently, Chase Bank invited you to participate in the ongoing online banking security protection survey. At Chase Bank, we......



This email is classified as phishing because it contains several red flags that indicate it may not be a legitimate communication from Ghase Baak. Here are some key indicators that subgest this small is phishing: 1. Sender's small address is not free a legitimate Chase Baak domain: The sender's mail address is not free a legitimate last Chase Baak domain, but rather free a generic domain such as "survey-essuruly" (e.gov". This is a common taction last's domain. To personal information: The sender of the survey-essure chain and the survey survey claining that the completed "as soon as possible" to help protect the customer's account information. This is a common tactic used by phishers to trick customers into divulging sensitive information such as login credentials of financial information. 3. Lack of personalization: The email does not contain may personalized information or references to the customer's determents of the customer's account activity.



Explanation: This email is legitimate as it contains the subject line "New Meek Urgent Security Survey" which indica tes that it is a survey sent by Chase Bank to gather feedback from its customers. The email also includes the sender 's name, Chase Bank, which matches the company mentioned in the subject line. Additionally, the email includes a lin k to the survey, which can be accessed by clicking on "Begin Survey". This link takes the recipient to a secure webs



Explanation:

 Suspicious Sender Email Address: The sender's email address "survey-e.sucurity@co.gov" does not match the off icial domain of Chase Bank, which is typically "@chase.com". The use of a government domain (".gov") in a phishing e mail is a common tactic to appear legitimate and trustworthy.

Urgency and Scarcity: The email creates a sense of urgency by stating that the survey will close once a sufficient number of responses are received. Phishers often use this tactic to pressure recipients into acting quickly wi
thout thinking critically about the email.

Figure 1. Snapshot of Model Input, Generated Explanation, and CC-SHAP Scores, with SHAP Values for Top Contributing Tokens During Prediction and Their Corresponding Values in the Explanation

Llama 7B predicted as legitimate for the same email. Along with these prediction, the explanation from each of these models are very different, each prioritizing different features as an major reason for their decisions, demonstrating differences in their underlying decision processes. The CC-SHAP score from different models varies even for same email ranging from 0.991 for Llama 7B and 0.900 for Llama 8B to 0.285 for Wizard 7B. The variance in CC-SHAP scores implies how model perceives and weighs different semantic and contextual cues while making classification and explanation reasoning. The different models identified different high-influencing tokens for their predictions and explanations. In case of Llama 7B and Llama 8B words such as "bank", "card", "protect", "quality", and "security" were prioritized and which aligns with phishing tactics which creates urgency. Likewise, Wizard 7B focused on "participate", "subscribe" and "update", as an indication of different weighting approach.

Based on the interpreted results, the findings align with our previous observation that high cc-shap score does not always correlate with accurate decision making.

7. Conclusion

This research study provides a comprehensive evaluation of LLM models highlighting the challenges in phishing detection, particularly in their explanability, consistency, and classification. We systematically evaluated the efficacy of three fine-tuning techniques: Binary Classification, Contrastive Learning, and Direct Preference Optimization (DPO), across multiple transformer-based architectures (BERT, LLaMA 7B, LLaMA 8B, and Wizard 7B) on combined Nazario and Enron phishing datasets. We found that binary classification was by far the most reliable approach, achieving the highest accuracy and lowest loss, whereas Wizard 7B lagged in generalization. Sim-

Phishing CC-SHAP (Mean ± Std Dev)	Ham CC-SHAP (Mean ± Std Dev)	Phishing Accuracy (%)	Ham Accuracy (%)
0.9659 ± 0.0304	0.9779 ± 0.0169	40.0	100.0
0.9549 ± 0.0523	0.9742 ± 0.0137	30.0	100.0
0.1231 ± 0.0906	0.1924 ± 0.1283	80.0	95.0
	Phishing CC-SHAP (Mean ± Std Dev) 0.9659 ± 0.0304 0.9549 ± 0.0523 0.1231 ± 0.0906	Phishing CC-SHAP (Mean \pm Std Dev) Ham CC-SHAP (Mean \pm Std Dev) 0.9659 ± 0.0304 0.9779 ± 0.0169 0.9549 ± 0.0523 0.9742 ± 0.0137 0.1231 ± 0.0906 0.1924 ± 0.1283	Phishing CC-SHAP (Mean ± Std Dev) Ham CC-SHAP (Mean ± Std Dev) Phishing Accuracy (%) 0.9659 ± 0.0304 0.9779 ± 0.0169 40.0 0.9549 ± 0.0523 0.9742 ± 0.0137 30.0 0.1231 ± 0.0906 0.1924 ± 0.1283 80.0

 TABLE 4. AVERAGE CC-SHAP SCORE FOR EMAILS WITH THEIR PREDICTION ACCURACY

 HIGHER THE CC-SHAP VALUES, BETTER THE TOKENS ALIGN

ilarly, Contrastive learning demonstrates minimal losses for BERT and for LLaMA 8B,yet delivers no accuracy gain over binary classification. DPO fine-tuning incurs very high losses for LLaMA 7B and for Wizard 7B and underperformed in phishing detection. These results show that rich embedding objectives alone must be paired with explicit classification supervision for reliable performance. In our CC-SHAP analysis, it is observed that LLaMA models score high on explanation-prediction token alignment (> 0.95), yet low on phishing accuracy (30% and 40%), whereas Wizard has lower token alignment but higher accuracy of 80% highlighting that explanation confidence alone doesn't predict real-world performance.

Our findings raise two crucial questions: "Should LLMs be designed to replicate human-like uncertainty, adopting the complexities of human decision-making? Or is it better they prioritize deterministic behavior to ensure consistency, reliability, and predictability? " [29]. With these questions as part of future direction, research should be more focused on developing LLMs that balance human-like uncertainty with reliability, ensuring both consistency and adaptability in decision making. Moreover, exploration on human-centric fine-tuning techniques and dynamic integration of LLMs and Cognitive models with improved evaluation metrics can help to understand the human perspective. This approach can facilitate more individualized training modules for phishing detection in the future.

References

- [1] K. Singh, P. Aggarwal, P. Rajivan, and C. Gonzalez, "Training to detect phishing emails: Effects of the frequency of experienced phishing emails," in *Proceedings of the human factors and ergonomics society annual meeting*, vol. 63, no. 1. SAGE Publications Sage CA: Los Angeles, CA, 2019, pp. 453–457.
- [2] S. Salloum, T. Gaber, S. Vadera, and K. Shaalan, "A systematic literature review on phishing email detection using natural language processing techniques," *IEEE Access*, vol. 10, pp. 65703–65727, 2022.
- [3] R. Dhamija, J. D. Tygar, and M. Hearst, "Why phishing works," in *Proceedings of the SIGCHI conference on Human Factors in computing systems*, 2006, pp. 581–590.
- [4] N. Q. Do, A. Selamat, O. Krejcar, E. Herrera-Viedma, and H. Fujita, "Deep learning for phishing detection: Taxonomy, current challenges and future directions," *Ieee Access*, vol. 10, pp. 36429– 36463, 2022.
- [5] T. Koide, N. Fukushi, H. Nakano, and D. Chiba, "Chatspamdetector: Leveraging large language models for effective phishing email detection," *arXiv preprint arXiv:2402.18093*, 2024.
- [6] F. Heiding, B. Schneier, A. Vishwanath, J. Bernstein, and P. S. Park, "Devising and detecting phishing emails using large language models," *IEEE Access*, 2024.
- [7] C. Lee, "Enhancing phishing email identification with large language models," arXiv preprint arXiv:2502.04759, 2025.
- [8] S. Jamal, H. Wimmer, and I. H. Sarker, "An improved transformerbased model for detecting phishing, spam and ham emails: A large language model approach," *Security and Privacy*, vol. 7, no. 5, p. e402, 2024.

- [9] J. Hazell, "Spear phishing with large language models," arXiv preprint arXiv:2305.06972, 2023.
- [10] K. Afane, W. Wei, Y. Mao, J. Farooq, and J. Chen, "Nextgeneration phishing: How llm agents empower cyber attackers," in 2024 IEEE International Conference on Big Data (BigData). IEEE, 2024, pp. 2558–2567.
- [11] M. Sharma, K. Singh, P. Aggarwal, and V. Dutt, "How well does gpt phish people? an investigation involving cognitive biases and feedback," in 2023 IEEE European Symposium on Security and Privacy Workshops (EuroS&PW). IEEE, 2023, pp. 451–457.
- [12] B. Lim, R. Huerta, A. Sotelo, A. Quintela, and P. Kumar, "Explicate: Enhancing phishing detection through explainable ai and Ilmpowered interpretability," arXiv preprint arXiv:2503.20796, 2025.
- [13] M. A. Uddin and I. H. Sarker, "An explainable transformer-based model for phishing email detection: A large language model approach," arXiv preprint arXiv:2402.13871, 2024.
- [14] P. Bountakas, K. Koutroumpouchos, and C. Xenakis, "A comparison of natural language processing and machine learning methods for phishing email detection," in *Proceedings of the 16th International Conference on Availability, Reliability and Security*, 2021, pp. 1–12.
- [15] J. Nazario, "Phishing email corpus," 2021, accessed: April 2021. [Online]. Available: https://monkey.org/~jose/phishing/
- [16] I. Chanis and A. Arampatzis, "Enhancing phishing email detection with stylometric features and classifier stacking," *International Journal of Information Security*, vol. 24, no. 1, pp. 1–16, 2025.
- [17] J. Zhang, H. Wen, L. Deng, M. Xin, Z. Li, L. Li, H. Zhu, and L. Sun, "Hackmentor: Fine-tuning large language models for cybersecurity," in 2023 IEEE 22nd International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom). IEEE, 2023, pp. 452–461.
- [18] X. Lin, W. Wang, Y. Li, S. Yang, F. Feng, Y. Wei, and T.-S. Chua, "Data-efficient fine-tuning for llm-based recommendation," in *Proceedings of the 47th International ACM SIGIR Conference* on Research and Development in Information Retrieval, 2024, pp. 365–374.
- [19] Z. Han, C. Gao, J. Liu, J. Zhang, and S. Q. Zhang, "Parameterefficient fine-tuning for large models: A comprehensive survey," *arXiv preprint arXiv:2403.14608*, 2024.
- [20] E. J. Hu, Y. Shen, P. Wallis, Z. Allen-Zhu, Y. Li, S. Wang, L. Wang, and W. Chen, "Lora: Low-rank adaptation of large language models," arXiv preprint arXiv:2106.09685, 2021.
- [21] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "Bert: Pretraining of deep bidirectional transformers for language understanding," in *Proceedings of the 2019 conference of the North American chapter of the association for computational linguistics: human language technologies, volume 1 (long and short papers)*, 2019, pp. 4171–4186.
- [22] A. Al Tawil, L. Almazaydeh, D. Qawasmeh, B. Qawasmeh, M. Alshinwan, and K. Elleithy, "Comparative analysis of machine learning algorithms for email phishing detection using tf-idf, word2vec, and bert," *Comput. Mater. Contin*, vol. 81, p. 3395, 2024.
- [23] M. AI, "Llama: Large language model meta ai," 2023, available on Hugging Face: https://huggingface.co/meta-llama/Llama-7b-hf.
- [24] ——, "Llama 3 8b model," https://huggingface.co/metallama/llama-3-8b, 2023, available on Hugging Face.
- [25] Dreamgen, "Wizard 7b: dreamgen/wizardlm-2-7b," Hugging Face Repository, 2024. [Online]. Available: https://huggingface.co/ dreamgen/WizardLM-2-7B

- [26] R. Rafailov, A. Sharma, E. Mitchell, C. D. Manning, S. Ermon, and C. Finn, "Direct preference optimization: Your language model is secretly a reward model," *Advances in Neural Information Processing Systems*, vol. 36, pp. 53728–53741, 2023.
- [27] P. H. Le-Khac, G. Healy, and A. F. Smeaton, "Contrastive representation learning: A framework and review," *Ieee Access*, vol. 8, pp. 193 907–193 934, 2020.
- [28] L. Parcalabescu and A. Frank, "On measuring faithfulness or self-consistency of natural language explanations," *arXiv preprint arXiv:2311.07466*, 2023.
- [29] J. Ma, "Can machines think like humans? a behavioral evaluation of llm-agents in dictator games," *arXiv preprint arXiv:2410.21359*, 2024.