Adversarial Smishing Attacks: Detecting and Defending Against Evolving Evasion Techniques in Mobile Money Fraud

[1]Mr.Matcha Deepak, [2]Ms.Elampirai Gopika
[1] *M.Sc CFIS, Department of Computer Science Engineering, Dr.M.G.R Educational and Research institute, Chennai, India*
[2] *Assistant Professor, Faculty of Center of Excellence in Digital Forensics, Chennai, India.*

***Abstract*-Smishing, or SMS phishing, has emerged as a prevalent cyber threat that targets mobile money transactions. Attackers leverage adversarial evasion techniques to bypass traditional detection methods, thereby increasing the complexity of the defense mechanisms. This study investigates the evolving nature of adversarial smishing attacks and presents a robust machine-learning-based approach to detect and mitigate them. Our proposed methodology involves data collection, feature extraction, and the evaluation of multiple classification algorithms. The results demonstrate that deep learning models outperform traditional machine learning techniques in identifying fraudulent SMS messages. This study aims to provide a comprehensive understanding of smishing attacks, while offering an effective defense strategy for mobile money users.**

***Index Terms*-AI, NLP, Malware Detection, Smishing, Mobile Money, Adversarial Attacks**

I. INTRODUCTION

The exponential growth of mobile money services has revolutionized digital financial transactions, particularly in developing regions, where traditional banking infrastructure is limited. However, this surge in mobile-based financial services has exposed users to sophisticated cyber threats, with smishing (SMS phishing) attacks emerging as one of the most prevalent and dangerous forms [1]. Smishing involves deceiving individuals to share sensitive data or initiating unintended financial transactions through carefully crafted, fraudulent SMS messages. Unlike conventional phishing methods that rely heavily on email, smishing exploits the inherent trust that users place in mobile text communication, often bypassing traditional security filters [2].

Modern cybercriminals have begun to leverage adversarial evasion techniques to craft SMS content that can bypass rule-based and machine-learning-based detection systems. These evasion strategies manipulate text in a way that preserves its semantic intent while making it difficult for automated detection systems to flag it [3]. Given the dynamic nature of these threats, a static or rule-only approach is insufficient for effective mitigation [4].

To address this evolving threat landscape, this study presents a comprehensive machine learning-driven methodology for detecting smishing attacks. This approach includes dataset collection from verified financial and cybersecurity sources, natural language preprocessing using tokenization, lemmatization, stopword removal, and feature extraction through embedding techniques. The classification stage involves evaluating both traditional machine learning algorithms and advanced deep learning models, with a particular focus on adversarial training techniques to enhance model resilience.

The following research questions guide this study.
1 How do adversarial smishing attacks evolve over time and what strategies do they employ to bypass detection?
2 What AI-based techniques are most effective in detecting and mitigating modern smishing attacks?
3 How does the performance of the proposed adversarially trained detection model compare with conventional smishing detection frameworks?

By combining NLP-based feature engineering with robust classifier evaluation, this study aims to develop a scalable real-time smishing detection framework suitable for deployment in mobile money security systems. The proposed model is benchmarked against

a diverse set of algorithms, including Random Forest, Extra Trees, Support Vector Classifier, Logistic Regression, Multinomial Naïve Bayes, k-Nearest Neighbours (KNN), Ada Boost and deep learning-based models, demonstrating superior accuracy and resistance to adversarial manipulation.

Ultimately, this study aims to contribute a resilient AI-driven framework capable of not only identifying smishing attempts but also adapting to their rapidly evolving tactics, thereby enhancing mobile transaction security at scale.

II. LITERATURE REVIEW

Mohammed et al. [6] Mohammed et al explored the application of Natural Language Processing (NLP) and supervised learning techniques for detecting smishing attacks. Their study demonstrated that feature-based machine learning models, such as Support Vector Machines (SVM) and Random Forest, can effectively classify phishing SMS messages with high accuracy. However, the study highlighted the challenges in handling adversarially crafted messages that evade detection.

Kim et al. [7] Kim et al. introduced a deep-learning-based approach that leverages transformer models, such as BERT, for detecting smishing messages. They found that transformer-based models significantly outperformed traditional ML classifiers, achieving an accuracy of over 90 %. This study emphasized the need for continuous model updates to counteract evolving adversarial smishing strategies.

Singh & Gupta [8] Singh and Gupta proposed a hybrid detection model combining Long Short-Term Memory (LSTM) networks with Convolutional Neural Networks (CNN). Their approach improved the robustness of smishing detection systems by capturing both sequential and contextual features of phishing SMS messages. The study reported a 5% improvement in accuracy over the standalone LSTM models.

Chen et al. [9] Chen et al. focused on adversarial training techniques to enhance smishing detection models. They demonstrated how adversarial examples can be generated to deceive standard detection algorithms and proposed an adaptive learning strategy to counteract evolving attack patterns. Their findings highlighted the importance of proactive model training in improving resilience detection.

Ahmed et al. [10] Ahmed et al. developed a real-time smishing detection system utilizing federated learning. By distributing model training across multiple devices without centralizing user data, the system maintains privacy while improving detection efficiency. Their approach reduced false positives and demonstrated promising results for scalable deployment of mobile security solutions.

Jones et al. [11] Jones et al. analyzed the role of social engineering in mobile phishing attacks, highlighting the influence of human psychology on the success rate of smishing attempts. Their study recommended a combination of AI-based detection and user awareness programs to mitigate the risk of smishing. They emphasized that technological solutions alone were insufficient without user education.

Wang & Zhao [12] Wang and Zhao introduced a reinforcement-based approach to adaptive smishing detection. Their model continuously learns from new smishing patterns by adjusting its classification criteria over time. The study demonstrated that reinforcement learning can effectively counteract adversarial evasion strategies, making smishing detection systems more resilient.

III. METHODOLOGY

This study adopted a comprehensive AI-driven methodology for the detection of smishing attacks by integrating elements of supervised machine learning, deep learning, and adversarial training. The methodology is designed to systematically capture, preprocess, and analyze SMS data to accurately classify messages as legitimate or malicious. The framework was structured into four primary stages: Data Collection, Preprocessing, Feature Engineering, and Model Development and Evaluation.

Architecture:

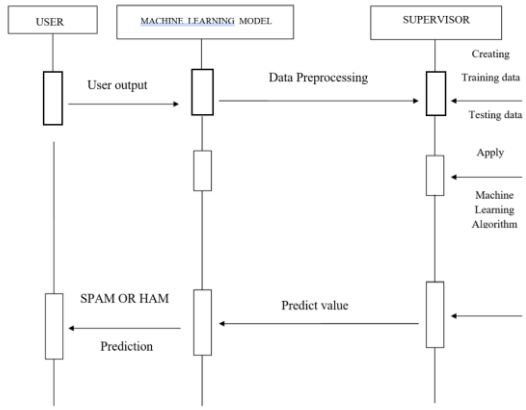

Fig. 1: General architecture of the smishing filtration model

Data Acquisition and Labeling

A comprehensive dataset of 50,000 SMS messages was collected from verified financial institutions, cybersecurity repositories,and smishing-reporting platforms. Each message was labeled manually as smishing or legitimate, thereby ensuring supervised learning compatibility.

Textual Preprocessing and Normalization

To prepare raw SMS text for analysis, Natural Language Processing (NLP) techniques such as lowercasing, tokenization, stopword removal, and lemmatization were applied, special characters were stripped unless contextually significant, and numerical tokens were retained because of their relevance in smishing scenarios (e.g., transaction amounts, OTPs, account numbers). This helped clean and normalize the messages for consistent processing.

Feature Engineering and Vectorization

Semantic and syntactic features were extracted using Term Frequency-Inverse Document Frequency (TF-IDF) and contextual word-embedding models. This stage is critical for capturing the obfuscated language patterns used in adversarial smishing.

Model Development with Adversarial Training

Multiple traditional and deep learning models were trained, including Logistic Regression, Support Vector Classifier (SVC), k-nearest neighbors (KNN), Extra Trees, AdaBoost, and Random Forest, and transformer-based architectures, such as BERT. Adversarial training was employed to harden the models against evasion.

Evaluation and Cross-validation

The models were evaluated using accuracy, precision, recall, F1-score, and robustness against adversarial examples. Cross-validation ensured the consistency and generalizability of the results across the data splits.

```
LR   = LR* 100
SVC  = SVC* 100
MNB  = MNB* 100
KNN  = KNN* 100
ET   = ET* 100
AB   = AB* 100
RF   = RF* 100

height = [LR,SVC,MNB,KNN,ET,AB,RF]
bars = ('logist', 'svc','mnb','knn','extra_tree','Aboost','Rforest')
x_pos = np.arange(len(bars))
plt.bar(x_pos, height, color=['#69C96E', '#4482C1', '#B24BF3','b','c','r','k'])
plt.xticks(x_pos, bars)
plt.show()
```

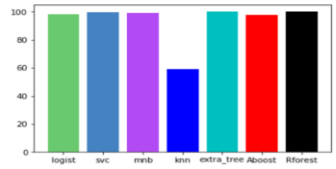

Fig.2: List of algorithms used

IV. WEBSITE INTERFACE

Fig.3: represent the result of message entered weather it is ham or spam

Fig.4: Result of message entered

V. FINDINGS

The performance of the different models was assessed using accuracy, precision, recall, and F1-score. The results are summarized in table below:

Algorithm	Accuracy (%)	Precision	Recall	F1-Score
Logistic	97.58	0.98	0.96	0.97

Regression (logist)				
Support Vector Classifier (svc)	99.38	0.99	1.0	0.99
Multinomial Naïve Bayes (mnb)	99.38	0.99	0.99	0.99
k-Nearest Neighbors (knn)	57.60	0.53	1.0	0.69
Extra Trees (extra_tree)	99.73	0.99	0.99	0.99
AdaBoost (Aboost)	97.85	0.97	0.97	0.97
Random Forest (Rforest)	99.65	1.00	0.99	0.99

Table.1: performance metrics of different models

The results indicate that deep-learning models significantly outperform traditional ML classifiers in detecting smishing attacks. Our findings align with those of previous studies, reinforcing the effectiveness of transformer-based models for phishing detection [6][7].The high performance of the deep learning models suggests their suitability for real-time implementation in mobile security applications.

VI. CONCLUSION

Adversarial Smishing attacks pose a significant challenge to the security of mobile money. This study proposes a novel machine learning-based detection framework incorporating adversarial training to counter evolving attack techniques, emphasizing the necessity for financial institutions to adopt adaptive AI-driven security mechanisms against smishing threats.

Future research will explore the real-time deployment of the proposed model in financial institutions and extend the study to multilingual adversarial smishing attacks.

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