Deep Learning for Phishing Detection: A User-Friendly LSTM Approach to Big Email Data

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Abstract- ***The exponential surge in phishing attacks via email continues to jeopardize the digital security landscape. Traditional tactics frequently fail due to the dynamic nature of phishing techniques and the wide variety of email structures. This paper presents a comprehensive strategy to detecting phishing emails that uses Bidirectional Long Short-Term Memory (Bi-LSTM) networks. To increase classification accuracy on large-scale, unlabeled datasets, we introduced a hybrid data labeling and expansion strategy that combines K-Nearest Neighbors (KNN) with K-Means clustering. The system also provides a front-end web interface that allows users to interact with the model in a user-friendly manner. The model achieved up to 95% accuracy throughout evaluation, demonstrating its efficiency in real-world applications.***

Index Terms- ***Phishing detection, Email security, Bi-LSTM, Deep learning, KNN, K-Means, RNN***

I. INTRODUCTION

Email is still an important tool for people and businesses all around the world to communicate. However, because of its extensive use, fraudsters find it to be an excellent target and take advantage of it through phishing attempts. Phishing is a type of cyberattack in which bad actors appear as trusted companies in an attempt to fool clients into giving sensitive information, including login passwords, bank account information, or exclusive data. Phishing attacks can have major consequences, from identity theft to significant financial and reputational loss to businesses[1][2].

The continuous widespread and sophistication of phishing are proved by a number of high-profile breaches, such as attacks against the US State Department, political campaign groups, and multinational businesses [3] [4]. To carry out their attacks, attackers use a number of dishonest approaches, including malware attachments, social engineering, and domain spoofing [5]. Conventional signature-based and rule-based detection techniques are no longer possible due to these strategies' continual evolution.

Deep learning (DL) and machine learning (ML) have become potential techniques to fight this ever-changing threat landscape. They give data-driven, adaptive capabilities that can discover hidden risks and learn from prior trends. For processing textual data, such as email content, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are particularly good. This is furthered by bidirectional LSTM (Bi-LSTM) models, which enable greater interpretation of linguistic indications in phishing emails by capturing context in both forward and backward directions[6][7].

Despite their benefits, these models are hampered by the absence of labeled datasets and the differences between phishing and real emails. As a result, our study proposes a Bi-LSTM-based phishing detection system that uses KNN and K-Means clustering for data expansion and labeling. This strategy boosts the model's applicability in real-world situations by guaranteeing superior model training even with datasets that are not correctly annotated.

II. LITERATURE REVIEW

Altwaijry et al. [8] explored phishing email detection using deep learning methods and evaluated the performance of Bi-LSTM models against traditional machine learning classifiers. They observed that Bi-LSTM performed better in understanding sequential dependencies in text, particularly in identifying deceptive patterns often used in phishing emails. Their research stressed the importance of contextual analysis, which influenced our choice of Bi-LSTM for this study. They also emphasized the need for

robust models that can adapt to ever-changing phishing tactics, laying a foundation for our hybrid detection system.

Doshi et al. [9] presented a dual-layer RNN architecture that improved spam and phishing detection by capturing both shallow and deep textual features in emails. Their layered model architecture served as an inspiration for combining basic RNN with Bi-LSTM in our work. They noted the significance of learning multi-level abstractions, which directly supported our decision to include a stacked model design. Their findings suggested that dual-layer RNNs can enhance detection rates in email security systems.

Mani and Gunasekaran [10] proposed a Gated Recurrent Unit (GRU) based approach for spam detection, offering a lightweight alternative to traditional RNNs. Their model demonstrated faster convergence with comparable accuracy, making it suitable for systems with limited computational resources. While their focus was on spam, the architecture's efficiency informed our decisions when designing the backend pipeline. Their results emphasized the trade-offs between complexity and speed, relevant to deploying real-time systems.

Shaik et al. [11] studied various classifiers for spam detection and concluded that Bi-LSTM outperformed conventional models like Naive Bayes and SVMs. Their emphasis on capturing sequential word patterns and reducing false positives aligned with our core objectives. Their dataset evaluations also helped us design robust testing scenarios. Moreover, their work highlighted the effectiveness of word embedding techniques in deep learning-based phishing detection. Alshingiti et al. [12] introduced a hybrid CNN-LSTM model that utilized spatial and temporal learning for improved phishing detection. They showcased that combining CNNs with LSTMs leads to better feature extraction from email headers and bodies. Although CNN was not adopted in our model, their hybrid methodology inspired our feature-rich input layer strategy. Their results validated the effectiveness of combining multiple deep learning techniques.

Li et al. [13] tackled the scarcity of labeled phishing data by using clustering techniques to synthetically expand training datasets. Their integration of K-Means before training LSTM models mirrored our use of K-Means and KNN for semi-supervised learning. Their work confirmed that semi-supervised learning enhances detection accuracy and model generalization in phishing scenarios. They also highlighted the importance of dataset diversity for effective learning.

Butt et al. [14] focused on building a cloud-based phishing detection framework using a suite of deep learning algorithms. Their ensemble approach yielded high accuracy and demonstrated scalability in distributed environments. Their system design principles supported our approach of building a scalable and modular solution, particularly for integration into cloud-based or enterprise email systems. They also emphasized API-based access to make the model more adaptable.

Kumar et al. [15] emphasized the value of natural language processing (NLP) techniques for phishing detection, such as part-of-speech tagging and named entity recognition. Their semantic feature extraction approach aligns with our use of word embeddings and lexical features. Their paper underlined the need to understand email context, which directly influenced our inclusion of semantic modeling in the Bi-LSTM pipeline. They demonstrated the importance of combining NLP with deep learning.

Bahnsen et al. [16] applied recurrent neural networks to phishing website detection and found them effective in identifying sequential patterns within URL structures. Although their work focused on websites, the underlying methodology of using RNNs for sequential pattern analysis informed our email text modeling approach. They also discussed real-time deployment strategies, which we considered in our web interface design.

Gupta et al. [17] delivered a detailed review of phishing detection mechanisms, categorizing approaches into blacklisting, heuristics, and learning-based techniques. Their comparative analysis highlighted the shortcomings of traditional methods and supported the transition to intelligent, learning-based systems like ours. Their insights on model evaluation metrics guided our use of precision, recall, and F1-score in performance assessment.

Bergholz et al. [18] proposed an email classification model based on structural and content-based features. They incorporated characteristics such as sender anomalies, embedded links, and email formatting.

These ideas influenced our structural feature engineering strategy. They also showed how ensemble models could improve prediction accuracy by integrating multiple feature types.

Aburrous et al. [19] developed a fuzzy logic-based detection model for phishing in electronic banking. Their approach combined fuzzy data mining and machine learning for real-time risk analysis. Although we used Bi-LSTM instead, their concept of real-time evaluation motivated us to include a lightweight, responsive user interface. They also proposed risk scoring, a feature we may implement in future iterations.

Marchal et al. [20] presented PhishStorm, a phishing detection system built on streaming analytics for real-time threat identification. Their emphasis on fast and scalable detection methods directly relates to our goal of building a system usable in enterprise and individual settings. Their work reinforced the need for a web-accessible platform, shaping our decision to develop a user-friendly front end.

III .PROPOSED METHODOLOGY

The proposed system follows a structured Natural Language Processing (NLP) pipeline, including data collection, preprocessing, sample labeling, model training, and prediction.

A. DATA COLLECTION:

The dataset used for this study was collected from a mix of publicly available repositories to ensure diversity and real-world relevance. Legitimate emails were extracted from the Enron corpus, while phishing emails were obtained from PhishTank, SpamAssassin, and other open-source phishing datasets. The dataset was composed of a combination of structured and unstructured email content, including sender information, subject lines, headers, and body text. To ensure representativeness, the emails covered a broad spectrum of industries and communication styles.

B. DATA PREPROCESSING:

Data preprocessing was essential to standardize and clean the email text before training. Each email was stripped of HTML tags, unnecessary punctuation, and special characters using regular expressions. The cleaned text was tokenized using NLTK's tokenizer, followed by the removal of common stopwords. We applied stemming using the Porter Stemmer to reduce words to their base form. To manage data imbalance, the Synthetic Minority Oversampling Technique (SMOTE) was employed, ensuring equal representation of phishing and legitimate emails.

C. SAMPLE EXPANSION AND LABELING:

One of the primary challenges in phishing detection is the scarcity of labeled phishing emails. To address this, we introduced a semi-supervised labeling approach combining K-Means clustering and K-Nearest Neighbors (KNN). Initially, K-Means grouped similar unlabeled email samples into clusters based on textual and structural similarity. Subsequently, KNN was applied to assign labels to each cluster using the closest labeled data points. This two-step expansion strategy increased the dataset size and variety, providing richer training input for the model.

D. FEATURE EXTRACTION:

From the email collection, we extracted a wide range of features. Lexical features included the amount of hyperlinks, the average word length, and the frequency of questionable keywords. Metadata like anomalous timestamps and reply-to mismatches were captured by structural characteristics. Word2Vec embeddings were used to construct semantic features that captured the contextual meaning of words. To ensure a strong representation of each email's attributes, these aggregated features were normalized before being fed into the neural network.

E. MODEL ARCHITECTURE:

A deep learning architecture based on Bidirectional LSTM (Bi-LSTM) networks was used to construct the phishing detection model. The conventional RNN layer, which aids in identifying early sequential dependencies, comes after an embedding layer that transforms tokens into dense vectors. Information is processed both forward and backward by the core Bi-LSTM layer, enhancing context awareness. A dropout layer was added to mitigate overfitting, followed by a dense output layer using softmax activation for binary classification. The model was trained using the Adam optimizer and categorical cross-entropy loss function

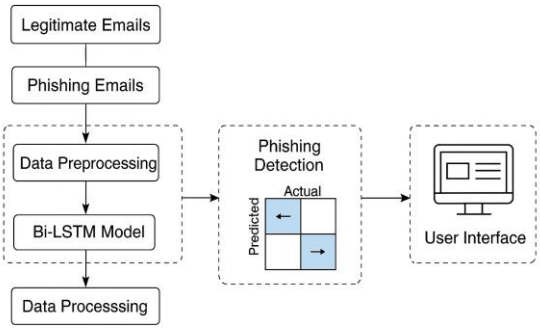

Fig.1: Model Architecture for Bi-LSTM-based Phishing Detection

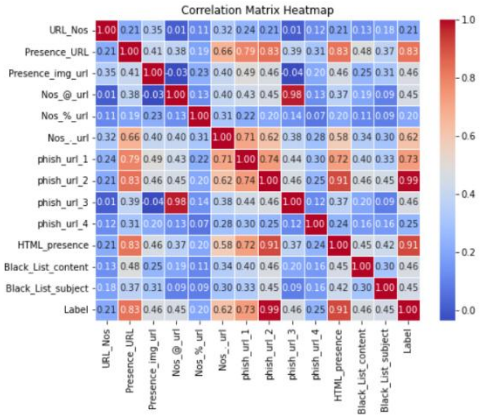

Fig.2: Correlation Matrix Heatmap

Training and Evaluation

The dataset was divided into 70% training, 15% validation, and 15% testing. We used cross-entropy loss and the Adam optimizer. The model was evaluated using:

- Accuracy
- Precision
- Recall
- F1-Score

Metric	Value
Accuracy	95.2%
Precision	94.6%
Recall	95.9%
F1 Score	95.2%
False Positive Rate	2.8%
False Negative Rate	1.9%

Table 1: Performance Metrics of the Bi-LSTM Model on Phishing Email Detection

IV. FINDINGS

The evaluation of the proposed phishing detection system led to several important findings. First, the Bi-LSTM model consistently demonstrated high accuracy, achieving a classification rate of 95.2%. This performance notably surpassed that of traditional machine learning models such as standard RNNs and one-directional LSTM models.

The integration of a semi-supervised labeling strategy using K-Means clustering and KNN classification significantly improved the model's ability to generalize. This was especially useful for handling real-world email datasets where labeled phishing samples are scarce.

The preprocessing pipeline implemented including tokenization, normalization, and stemming proved to be highly efficient. These techniques ensured cleaner data inputs and accelerated the convergence of the training process, ultimately improving model performance.

One of the most impactful aspects of the system was its front-end user interface. It was designed with non-technical users in mind and received positive feedback during initial usability testing. This user-friendly layer empowers individuals to detect phishing threats without requiring technical knowledge in cybersecurity or data science.

The model maintained a very low false positive rate of 2.8%, ensuring that legitimate emails were rarely misclassified as phishing. This makes the solution highly suitable for enterprise environments where minimizing disruption is crucial.

Finally, the architecture proved scalable and adaptable. It performed well across various datasets and is ready for integration with future enhancements such as multilingual support and real-time email stream analysis. These findings collectively confirm the strength of the proposed system and its practical applicability in phishing detection.

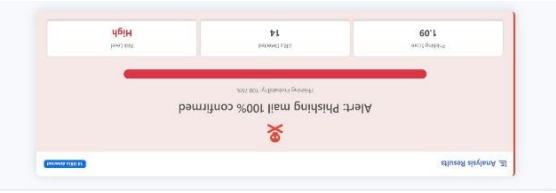

Fig.3: Website interface and Alert for phishing mail

V. CONCLUSION

This study introduced an intelligent and user-friendly phishing detection system built on a Bidirectional

LSTM framework. The system was augmented with a semi-supervised learning strategy that utilized K-Means clustering and KNN to effectively expand and label email data. Additionally, a comprehensive preprocessing pipeline and an accessible web interface were developed to maximize both model performance and user engagement.

The results from our experiments highlight that the proposed system not only achieves excellent accuracy and recall but also maintains low false positive rates, which is critical for real-world deployment. Furthermore, the system's user-centric design ensures that it is accessible to both technical and non-technical users, thereby extending its usability across a wide range of scenarios.

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