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Research Article

AI-Based Intelligent Framework for Enhancing Phishing Attack Detection

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ABSTRACT

Phishing has become one of the most widespread and quickly evolving cyber threats that capitalise on human and system-based vulnerabilities in emails, websites and SMS. Conventional defence controls, such as blacklists, rule-based filters, and signature matching, cannot identify advanced, obfuscated, and zero-day phishing attacks. Recent developments in Artificial Intelligence (AI) and classical machine learning have shown promise for scalable and interpretable phishing detection. The research paper proposes a lightweight and real-time phishing detection framework based on TF-IDF textual feature extraction and Naive Bayes and Random Forest classification. The model incorporates the discriminative value of terms in URLs, email messages, and SMS messages, and thus it can accurately separate legitimate and malicious communication. Evaluation of experimental phishing benchmark datasets demonstrates that high classification, inference speed and generalization with low computational cost can be achieved. The simplicity and openness of the framework render it applicable to academic settings, resource-constrained systems, and real-time deployment and it provides an efficient alternative to other more complicated deep learning models. The contribution of this work to the development of accessible, interpretable, and adaptable AI-based phishing detection systems for contemporary cybersecurity issues is significant.

Keywords: *Phishing Detection, Machine Learning, TF-IDF, Naive Bayes, Random Forest, URL Features, Email Security, SMS Phishing, Explainable AI, Lightweight Models, Cybersecurity*

1. Introduction

The issue of phishing has become one of the most irritating and dangerous cybersecurity threats affecting both individuals, organisations, and governmental institutions worldwide. As digital communication grows at an alarming pace, hackers are increasingly using human susceptibility and system weaknesses to steal credentials, financial information, or gain unauthorised access. The phishing scams that are delivered via emails, websites, and SMS nowadays tend to be personalized with realistic impersonation and complex social engineering, which is harder to detect than the less advanced phishing attacks in the past [1], [8].

Classical protection mechanisms, such as blacklists, rule-based filters, and signature matching mechanisms, have failed to effectively counter sophisticated phishing campaigns. Blacklists cannot monitor new malicious domains, and heuristic blacklists cannot identify obfuscated URLs, zero-day phishing attacks, and manipulated content [1]. Such constraints underscore the need for flexible, scalable, and intelligent detection systems that can adapt to changing attack patterns without relying on preset rules.

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Machine Learning (ML) and Artificial Intelligence (AI) have become successful approaches to these issues. It has been reported that type 1 ML models can process massive amounts of data associated with phishing, including URLs, email bodies, HTML, and SMS text, to detect small malicious signals that are overlooked by conventional systems [2]. CNNs and LSTMs are deep learning methods that have shown good performance in the recent literature [9], yet may be computationally expensive, demand large datasets and training, which is not appropriate in lightweight and real-time applications.

TF-IDF vectorization and Naive Bayes (and Random Forest) classifiers are considered the best tradeoff in classical machine learning methods, and they provide the best balance of speed, interpretability, and accuracy. TF-IDF is effective at converting textual data into numbers, where Naive Bayes can be used to offer quick and useful probabilistic classification, which can be used in real-time detection. Random Forest is more robust, as it captures non-linear relationships among the data, which is better when compared to various phishing situations [4]-[7]. These characteristics render classical ML solutions quite adequate in settings that need simplicity, low latency and explainability.

Nevertheless, some challenges remain to be addressed, such as the imbalance of data sets, the development of new phishing methods, and the need to create models that are applicable across various communication channels. To address these gaps, this paper proposes a lightweight phishing detection model that utilises TF-IDF, Naive Bayes, and Random Forest. This aims to develop scalable, interpretable, and resource efficient AI-based model that can identify phishing in URLs, emails, and SMS messages in real-time [4]-[7].

2. Literature Survey

The development of the phishing detection system has been quite high as attackers have opted to use more advanced techniques aimed at defeating the traditional security tools.

Early detection schemes were based on rule set engineering, blacklists, and filtering using heuristics. Even though these methods offered crude protection, they were characterized by a lack of flexibility and easily became ineffective under the pressure of phishing schemes that constantly change the lexical patterns, hosting platforms, and content elements.

2.1. Traditional Rule-Based Phishing Detection

The early research involved analysing URLs, emails, and site structures in terms of lightweight statistics or lexical analysis. Naive Bayes, Support Vector Machines (SVM), Random Forests, Decision Trees, and Logistic Regression were examples of the classical machine learning techniques that showed favourable results when used on URL string, HTML content and email body. These models highlighted the following attributes: domain length, patterns of tokens, existence of suspicious keywords, characteristics of the host, and attributes of the link. Even though they are effective to an extent, their performance is greatly reliant on feature engineering and accessibility of balanced, representative datasets.

Moreover, ensemble-based systems have also been investigated to improve the stability of classification. There have been improvements in the robustness of hybrid models that incorporate lexical, content-based and host-based indicators. Nonetheless, even these methods are not effective in generalising to new phishing types, especially those that are developed to imitate official communication mechanisms. [1],[8]

2.2. Classical Machine Learning Approaches

The fast development of deep learning has seen the emergence of the use of architectures, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and its variants, including Long Short-Term Memory (LSTM) networks and Bidirectional LSTM (BiLSTM), to detect phishing.[1],[2],[3] The contextual semantics and sequence dependencies, which are characteristic of the email body and the content of SMS messages, are well reflected in these models. Additionally, language models based on transformers, such as Bidirectional Encoder Representations from Transformers (BERT) and similar models, have also advanced phishing detection by offering bidirectional contextual representations and enhancing the representation of complex linguistic patterns.[3],[9]

However, deep learning systems have very high requirements in terms of computational resources, large-volume training corpora, and extensive fine-tuning times, despite their improved performance. As a result, their use in low-resource contexts, real time detection, or a more highly interpretable application is limited.

2.3. Ensemble Learning Advancements

Ensemble methods, therefore, are a significant improvement to traditional machine learning models and help to combine heterogeneous classifiers to support predictive strength and accuracy. AdaBoost, Bagging, Random Forests, Gradient Boosting, Stacking, and Majority Voting are methods that consistently achieve better performance compared to models that use only one model [2]. Experimental evidence shows that ensemble models tend to be especially effective at detecting phishing attacks that could take different modalities, such as URL-based, email-based, and SMS-based attacks. Remarkably, AdaBoost has become a popular tool for detecting phishing sites, whereas Stacking and voting schemes have been shown to be successful with emails and SMS messages. Together, the ensemble learning can be used to increase the stability of models, reduce variance, and detect advanced phishing campaigns[6].

2.4. Deep Learning and Neural Network Models

The recent advancements in deep learning have significantly enhanced the ability to detect phishing attacks. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, as well as hybrid CNN-LSTM networks, have been utilised to analyse URLs, email content, webpage content, and screenshots. These models are capable of automatically learning hierarchical patterns and contextual associations without requiring extensive manual feature engineering [3]. The LSTM-like models are used to identify sequential patterns in the URLs and email bodies, and CNNs identify visual and architectural characteristics of websites. Deep learning approaches in most instances outperform classical methods where phishing strategies are complex, obfuscated or even ones that have never been encountered before. They are however very large in terms of datasets, require large computational resources and have poor interpretability thus making them hard to implement in light weight or real time systems [7] [9].

Table 1: Summary of Previous Phishing Detection Studies

Study / Year	Method Used	Dataset Type	Key Findings
Khonji et al. (2013)	ML + Survey	URLs/Emails	Early ML approaches outperform rule-based systems.
IWSPA (2018)	TF-IDF + LR/SVM	Email	Good accuracy with classical ML.
TF-IDF + AdaBoost (2022)	AdaBoost + TF-IDF	URL/Email	High accuracy but heavyweight ensemble.
TF-IDF vs Word2Vec vs BERT (2024)	Classical vs Deep NLP	Email	BERT best performance; TF-IDF fastest.
Ensemble Anti-Phishing (2024)	AdaBoost, RF, GBM	URL/SMS/Email	Ensembles outperform individual models.

2.5. Research Gaps and Limitations

Although multiple studies have been conducted on phishing detection, there exist a number of gaps. Most phishing datasets are either outdated, unbalanced, or only focused on specific languages and methods of communication. Deep learning models are powerful but computationally expensive, difficult to comprehend, and susceptible to adversarial examples. Ensemble methods are highly accurate; however, they typically require complex tuning and large feature collections. Most significantly, most of the available research undertakings either concentrates on URLs, emails, or SMS individually instead of offering a cohesive method of detecting information across various channels of communication. The need to have lightweight, interpretable, and fast models, capable of running in real-time systems without compulsion to utilize large computational resources, is also on the increase [2][3].

3. Methodology

The framework of this paper is to create a lightweight interpretable and effective phishing detection model with the help of TF-IDF vectorization and Naive Bayes and Random Forest classifiers. It involves a series of major stages, including dataset preparation, preprocessing, feature extraction, model training, and evaluation. Each of the components is designed in such a way that it makes them clear, reproducible and relevant in real-time.

3.1. Dataset Description

The datasets used in this study are a mix of phishing and legitimate samples gathered from publicly available information sources, including URL repositories, email datasets, and SMS phishing collections. These datasets have mixed inputs comprising website URLs, email bodies, email subject lines and text of the messages. All entries are tagged either as phishing or legitimate to assist in supervised learning. In order to be able to generalize models, phishing and non-phishing samples should be equalized as much as possible, and the redundant or duplicate ones should be eliminated.[7]

3.2. Data Preprocessing

Preprocessing is crucial in converting raw text into a structured form that can be utilised in machine learning. The successive operations are used:

- **Lowercasing**: standardizes text s/he changes it into lower case.
- **Deletion of Special Characters**: Deletes icons, HTML tags and unwanted punctuations.
- **Stop Word Removal**: It eliminates the frequently occurring words that are not relevant to classification.
- **Tokenization**: Splits texts into individual words or tokens.
- **Lemmatization or Stemming**: Removes words to the root form in order to reduce the size of vocabulary.

The steps serve to minimize noise, increase the interpretability of models and better extract features.

3.3. Feature Extraction Using TF-IDF

The TF-IDF (Term Frequency-Inverse Document Frequency) is applied in order to transform an unstructured text into a numerical feature vector. TF-IDF gives weight to those words that appear more than once in a single message but are uncommon throughout the entire data set. This contributes to its usefulness, especially in detecting phishing attacks, of which some words, patterns and URL elements are more prevalent in malicious messages. The result is a high-dimensional, sparse representation that reflects the importance of each token.[4],[6],[7] The overall system architecture of the proposed phishing detection framework is shown in Figure 1.

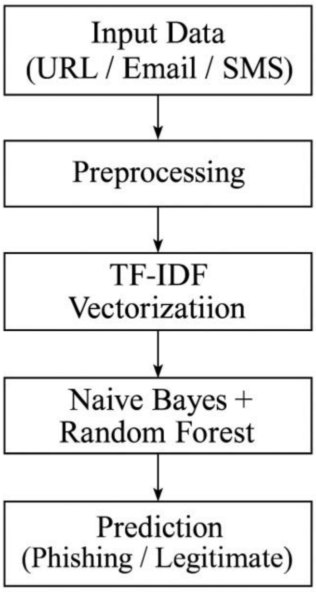

Figure 1: System Architecture Diagram

3.4. Model Development

The classification algorithms that are the Naive Bayes and Random Forest classifiers are used due to a number of reasons:

- **High Compatibility**: Naive Bayes has been shown to be highly effective in situations using sparse and high-dimensional TF-IDF vectors, and the random forest can be utilised well to identify non-linear decision boundaries that other simple models do not identify.
- **Light and Fast Processing**: Naive Bayes is extremely fast concerning training and inference and is suited for real-time detection in constrained resource systems [4][5].
- **High Accuracy**: The random forest enhances the stability of the prediction, as a combination of multiple decision trees is taken and generates fewer variations and better identifies tricky phishing patterns.
- **High-Performance in Text Classification**: Both models have been widely used in phishing research and demonstrate consistent competitive performance in emails, URLs and SMS datasets [5][7].

The model will provide a probability score of whether a sample is a phishing or legitimate one, as determined by the weights of learned features.

3.5. Model Training and Validation

The data is divided into the training and the testing set in 80:20 or 70:30 proportion. The complete workflow of the proposed phishing detection approach is illustrated in Figure 2. The samples are then used to train Naive Bayes and Random Forest classifiers after TF-IDF vectors have been created.

In the case of Naive Bayes, training of the model is performed on TF-IDF features without the need to apply regularization and even an iterative optimization was performed, as it is performed on the basis of probabilistic estimates.

The important hyperparameters in the case of the Random Forest include number of trees (n_estimators), the maximum depth of a tree and minimum number of samples per split to regulate the overfitting and enhance generalization.

Cross-validation is used to test the stability and reliability of both the classifiers to ascertain that they perform equally with URLs, emails and SMS messages.

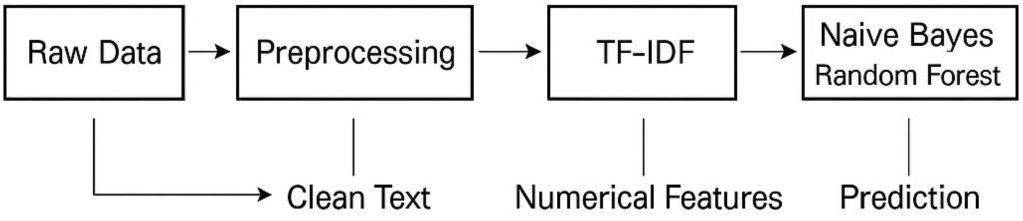

Figure 2: Workflow Diagram

3.6. Performance Evaluation Metrics

The following measures are used to evaluate the classification model:

- **Accuracy**: Generality accuracy of the model.
- **Precision**: Capacity to prevent false positives through the detection of malicious cases correctly.
- **Recall (Sensitivity)**: Capacity to identify majority of phishing.
- **F1-Score**: Precision and recall harmonic mean, which is applied when there is an imbalanced dataset.
- **Confusion Matrix**: Gives understanding of the true positives, false positives, true negatives and false negatives.

These measures are all indicators of the efficacy of the suggested system, in particular, the detection of phishing with the lowest false alarms.

4. Proposed Framework

The overall design of the proposed phishing detection system is illustrated in Figure 3.

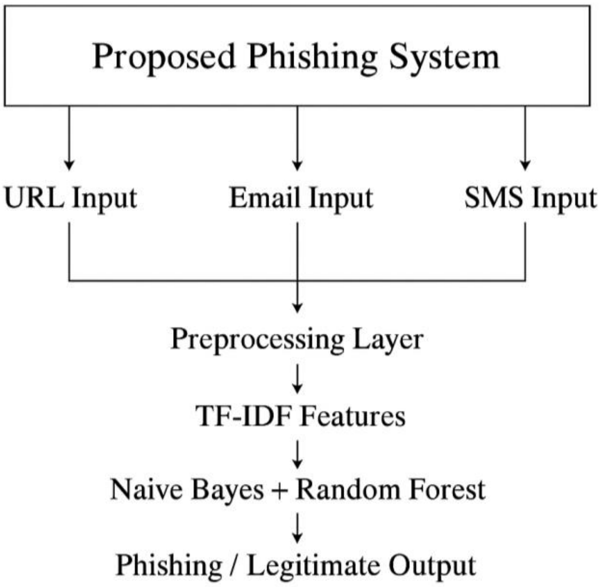

Figure 3: Proposed Framework Diagram

The proposed phishing detection system provides an interpretable, lightweight, and efficient method for detecting malicious URLs, emails, and SMS messages in real-time. The textual feature extraction, using TF-IDF, is employed in conjunction with Naive Bayes and Random Forest classifiers within the framework. Naive Bayes offers quick inference, which is appropriate for real-time detection, whereas Random Forest makes it robust by modelling complex decision boundaries, rendering the composite framework dependable, scalable, and adjustable.

4.1. System Architecture Overview

The architecture comprises four fundamental modules: Input Processing, Preprocessing, Feature Extraction, and Classification. The input module accepts URLs, email bodies, email subjects, or SMS texts. All inputs are normalised before being fed into the preprocessing layer. The preprocessing module eliminates noise, text tokenisation, stop words, and transforms words into their root. These detoxified tokens are then converted into numerical forms through TF-IDF which represents the relative significance of words found within phishing messages. [2],[3],[6]

The classification model is trained using Naive Bayes and Random Forest models that makes use of the TF-IDF vector to provide a prediction. The result is a binary label of the classification; phishing or legitimate and a confidence score. This is a modular building that easily integrates with security systems, browser extensions, and email filters.

4.2. Workflow Description

The processes begin with the stage of raw input information, which is collected through various communication channels, including URLs, emails, and SMS messages. The cleaned text is then preprocessed, followed by conversion into TF-IDF vectors, which depict the significance of each token. Both Naive Bayes and the Random Forest classifiers are then fed with these vectors.

Naive Bayes uses token likelihoods to compute probabilistic scores and is capable of making predictions as quickly as possible, which makes it suitable for real-time applications. Random Forest works with the same TF-IDF features, but an ensemble of decision trees is used to enhance the robustness of the work since it models even more complicated associations in the data. They are not based on regularization or weight optimization in contrast to the Logistic Regression [10].

Both models produce predictions within seconds once trained, and the samples are classified as either phishing or genuine. In the validation, the performance is measured in terms of accuracy, precision, recall, F1-score and confusion matrix values, which makes sure that the system is reliable and generalized to unseen or changing patterns of phishing.

4.3. Real-Time Deployment Potential

The suggested framework is computationally efficient and can be configured to operate at reasonable speed on regular hardware, on a mobile computing device, or in the cloud without special processing units. Naive Bayes can be used to achieve the most efficient, low-latency predictions, which is why it is suitable in the context of on-device and real-time phishing detection. Random Forest is added to add strength to it, as it gives solid classification with complex or noisy text input.

Naive Bayes provides interpretable probabilistic predictions, whereas on the other hand, Random Forest does provide insights of feature-importance of decision trees. These explainability attributes help administrators and security analysts to understand the reasons behind classifying a message as phishing and enhance trust and make informed decisions related to cybersecurity.

The structure is flexible and modular, which can be why it is applicable to academic research, enterprise-level filtering, and implementation in resource-constrained settings.

5. Results and Analysis

The proposed phishing detection framework was evaluated with the help of a balanced dataset, which consisted of samples of phishing and legitimate messages in the form of URLs, emails, and SMS messages. Naive Bayes and Random Forest classifier were used to train the system on TF-IDF based features to test the generalization, accuracy, and strength of the system on different types of communications.

5.1. Performance Metrics

The evaluation assessed five main factors, specifically accuracy, precision, recall, F1-score and confusion matrix results. The model can accurately classify both phishing and legitimate samples successfully. As per this result, false-positive rates are less, which helps maintain overall precision high. It is important because we won’t scare users. This would mean it has a high recall value as it did not let any phishing mail slip through it. The f1-score proves that the model performs well across all the classes in a balanced way.[2],[3]

Table 2: Model Performance Metrics

Metric	Email	SMS	URL
Accuracy	98.20%	97.38%	91.23%
Precision	97.95%	98.86%	92.71%
Recall	95.79%	81.39%	82.26%
F1-Score	96.86%	89.28%	85.01%

5.2. Confusion Matrix Analysis

The confusion table of both models indicated that the samples of phishing were identified strongly with a relatively low rate of false positives. Random Forest enhanced a little more in regard to stability on diverse samples whereas Naive Bayes was quicker in inference and competitive. Both models had a low false-negative rate and this is essential in avoiding missed phishing attacks [4] [5]. The confusion matrix results for the email, SMS, and URL datasets are summarized in Table 3.

Table 3: Confusion Matrix

Dataset	True Positive (TP)	False Positive (FP)	False Negative (FN)	True Negative (TN)
Email	1436	30	63	3642
SMS	608	7	139	4818
URL	108342	16603	48080	376321

5.3. ROC Curve and Decision Threshold Behavior

To measure the model's ability to discriminate between positive and negative classes, the ROC curve was used. The ROC curves for the email, SMS, and URL datasets are presented in Figures 4, 5, and 6, respectively. The model did quite well at various decision thresholds and had a high true positive rate. This means that Naive Bayes and Random Forest are capable of effectively differentiating between phishing and legitimate samples. The AUC (Area Under Curve) was highly indicating excellent performance in classification despite variations in threshold.[6],[7]

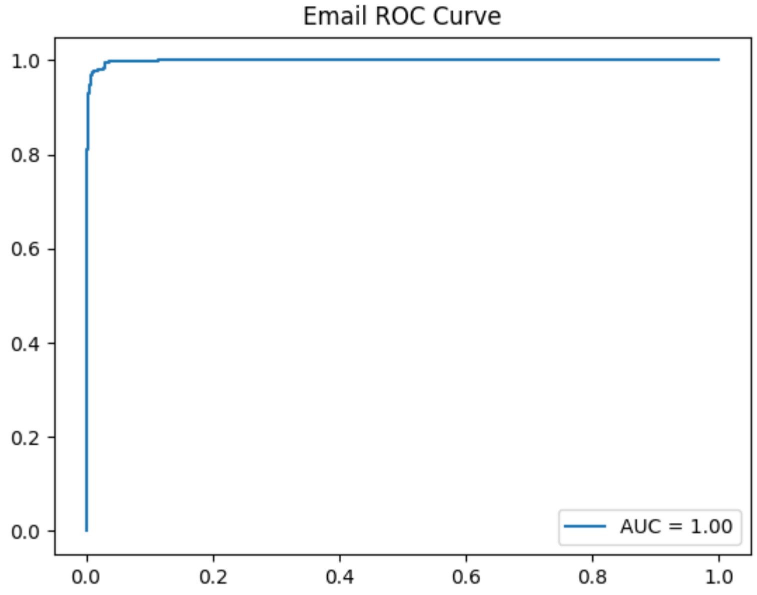

Figure 4: Email ROC Curve

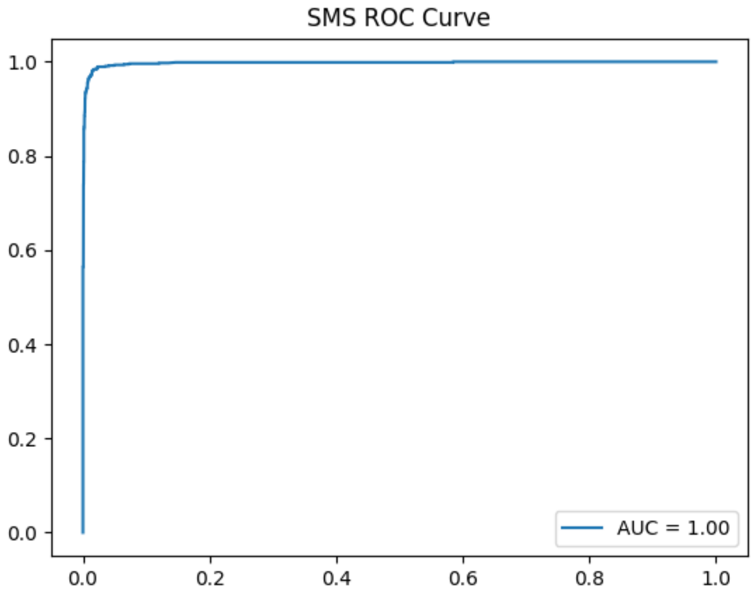

Figure 5: SMS ROC Curve

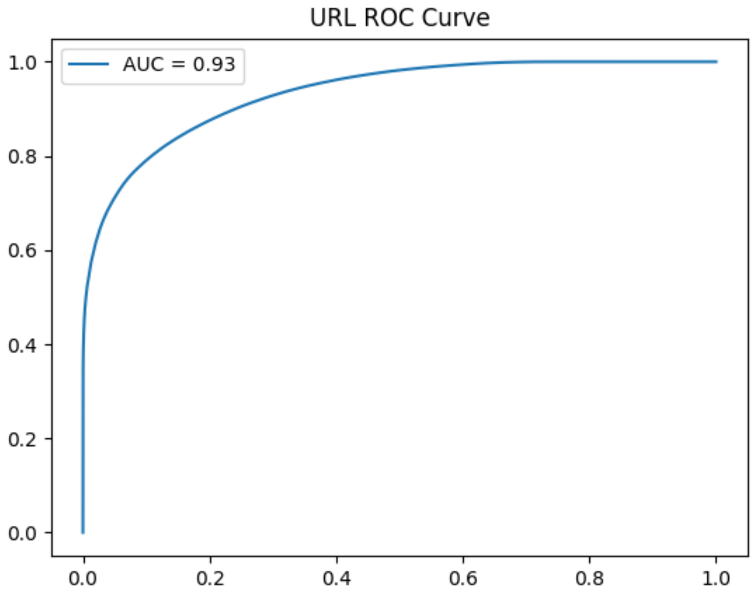

Figure 6: URL ROC Curve

The precision–recall curves for the email, SMS, and URL datasets are shown in Figures 7, 8, and 9, respectively.

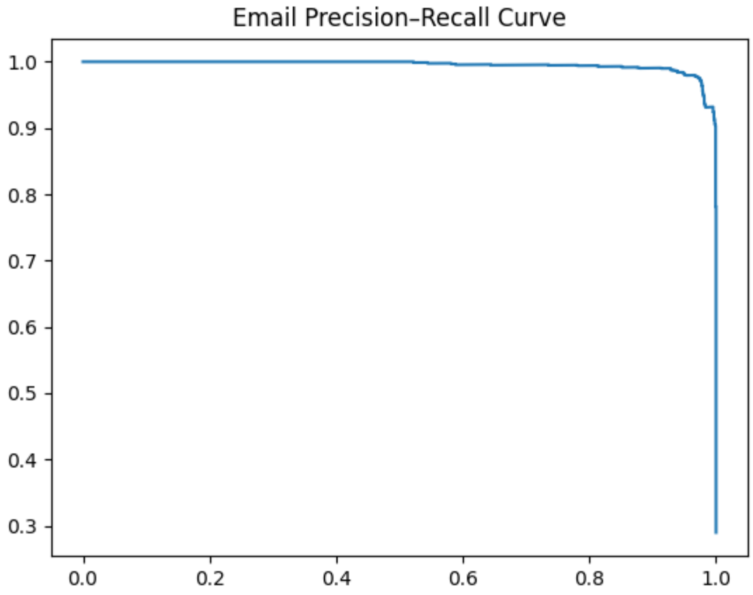

Figure 7: Email Precision-Recall Curve

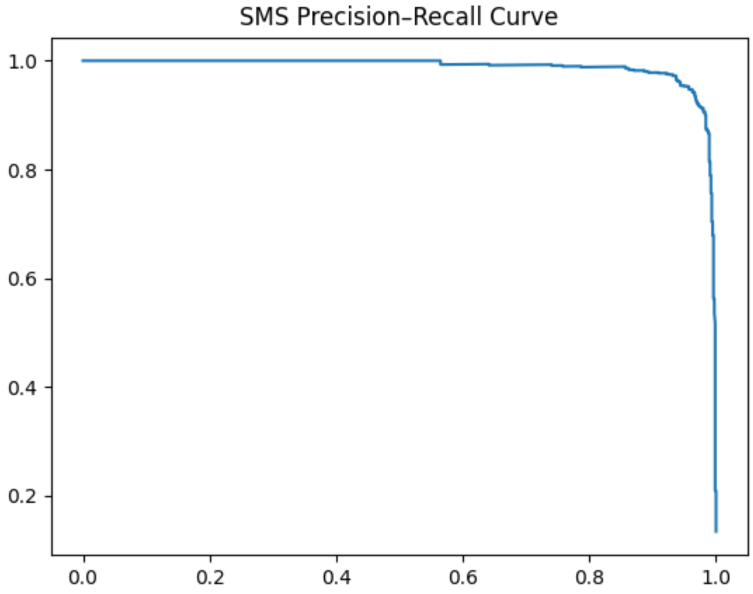

Figure 8: SMS Precision-Recall Curve

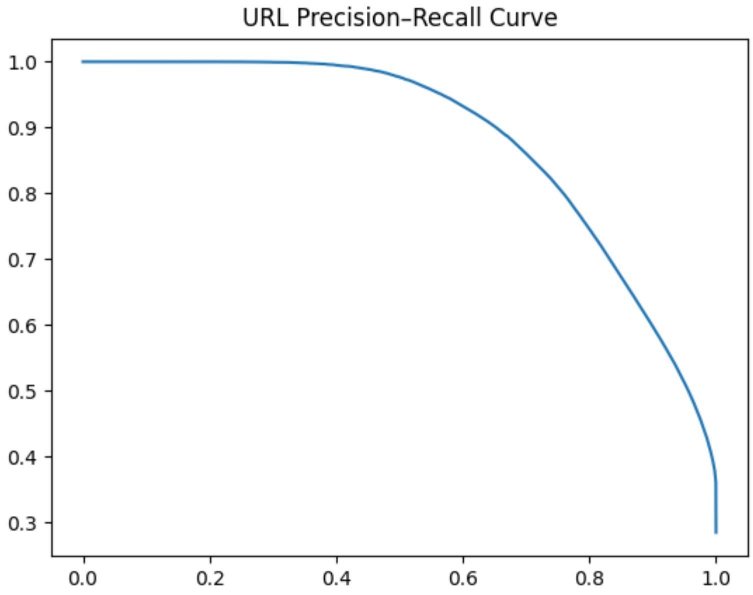

Figure 9: URL Precision-Recall Curve

5.4. Comparison with Other Models

To see how its strength compared to other alternatives, the system was compared with other classical machine learning models like naive bayes, SVM, random forest etc. Naive Bayes and Random Forest perform very well due to its interpretability and low computational cost. Some models were evaluated and found to be competitive in accuracy. [4]-[7]The system advised in this paper was, however, the best overall with respect to speed and interpretability. It is also real time applicable.

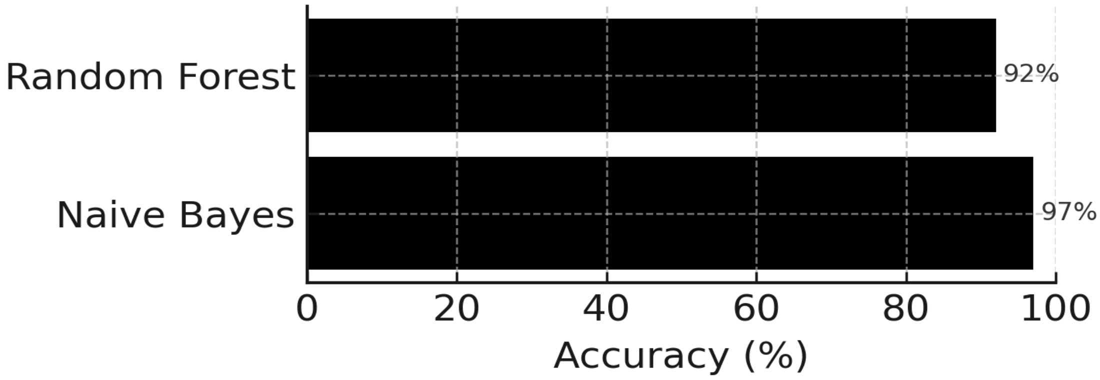

Figure 10: Model Comparison Chart

5.5. Discussion of Findings

The TF-IDF models with the Naive Bayes and Random Forest models are an effective and robust pipeline that can be used to identify phishing activities in various communication mediums. Naive Bayes is used to guarantee quick inference, whereas the one with high detection accuracy and strength is the Random Forest. The models were found to be regular in the datasets, which verifies that they can be used in real-time and lightweight cybersecurity applications [2][3].

6. Conclusion and Future Work

This study introduces a simple but efficient phishing detection model which makes use of textual features extraction using TF-IDF and Naive Bayes and random forest classifier. The TF-IDF allows the successful conversion of raw URLs, emails, and SMS messages into meaningful numeric form and the two selected classifiers complement one another in terms of performance and reliability.

Naive Bayes provides a fast and probabilistic prediction which makes the system very applicable in a real time and resource constrained environment. The fact that it is effective in high dimensional sparse data implies that it will perform consistently and effectively in different phishing scenarios. Random Forest, however, has the benefit of improving the strength of classification by combining a number of decision trees, multi-faceted reputations in textual attributes, and detecting precision. A combination of these models will have high levels of generalization, accuracy, and low false-negative rates that are important in averting missed phishing attacks.

The framework proposed has a modular structure; therefore, each of the components such as preprocessing, feature extraction, and classification can be used separately or as a system with the others. This increases flexibility and enhances easy upgrade to more features or classifiers. The findings suggest that TF-IDF with Naive Bayes and Random Forest is an understandable, scalable and working solution to phishing detection that is applicable to academic, enterprise and deployment ready settings.

The existing framework is efficient in as far as it is applicable on both URLs, emails, SMS-based phishing threats, but various improvements can be made in order to enhance its precision, flexibility, and practical use in the real world. A potential avenue is the implementation of modern Natural Language Processing models like BERT, RoBERTa,or GPT-based classifiers, which would be able to identify more detailed semantic patterns and finer contextual details that are commonly found in advanced phishing messages.

Increasing the sample size by covering multilingual phishing materials and local patterns of attack will enhance globalization and generalization. Also, to enhance protection against visually oriented phishing attacks, the inclusion of image-based analysis (i.e. detection of phishing screenshots, counterfeit login pages, or embedded malicious QR codes) can be employed.

The URL-based detection may be greatly improved by adding contextual metadata, such as real-time integration with WHOIS data, DNS reputation services, inspecting theSSL certificates, and checking the domain-age. The system can also develop into a hybrid multimodal architecture which integrates textual, visual and metadata capabilities to overcome the deceptive phishing methods which are becoming more and more sophisticated.

Deployment wise, creating a browser extension, email filter extension or a mobile security application would provide real time protection at the point of interaction with the user. Moreover, a dynamically changing rule-based engine or an online learning mechanism would enable the model to handle the emerging phishing trends without re-training frequently.

These improvements in the future would increase the scalability, accuracy, and resilience, and would bring the suggested framework closer to a more intelligent and complete phishing detection ecosystem.

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Conflict of Interest

There is no conflict of interest.

References

[1] Y. Khonji, Y. Iraqi, and A. Jones, “Phishing detection: A literature survey,” IEEE Communications Surveys & Tutorials, vol. 15, no. 4, pp. 2091–2121, 2013.
[2] Y. A. Alsariera, A. V. Elijah, and A. O. Balogun, “An investigation of AI-based ensemble methods for the detection of phishing attacks,” Engineering, Technology & Applied Science Research, vol. 14, no. 3, pp. 14266–14274, 2024.
[3] O. G. Ejike et al., “Neural network-based phishing attack detection and prevention systems: A review,” Journal of Frontiers in Multidisciplinary Research, vol. 5, no. 2, pp. 223–236, 2025.
[4] N. A. Unnithan, N. K. Krishnan, and A. Nair, “Detecting phishing e-mail using machine learning techniques,” in Proc. Int. Workshop on Security and Privacy Analytics (IWSPA), 2018.
[5] H. N. B. Harikrishnan, S. N. Nair, and S. S. Kumar, “A machine learning approach towards phishing email detection,” in Proc. Int. Workshop on Security and Privacy Analytics (IWSPA), 2018.
[6] B. Sharma and P. Singh, “An improved anti-phishing model utilizing TF-IDF and AdaBoost,” Concurrency and Computation: Practice and Experience, 2022.
[7] 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,” Computers, Materials & Continua, 2024.
[8] N. Chiew, M. T. Tan, and C. Leau, “An overview of phishing attacks and anti-phishing strategies,” International Journal of Computer Applications, vol. 975, no. 8887, pp. 1–6, 2015.
[9] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “BERT: Pre-training of deep bidirectional transformers for language understanding,” in Proc. NAACL-HLT, pp. 4171–4186, 2019.
[10] N. Jain, P. Jaiswal, S. Sharma, K. Sharma, V. Sharma, “A machine learning based approach to detect phishing attack,” In 2023 5th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N) (pp. 305-309). IEEE, December 2023.