

## Enhanced Phishing Email Classification through Multi-Level Feature Fusion

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### ABSTRACT

Phishing emails remain one of the most common cyber threats. It causes serious financial damage, information theft, and security vulnerabilities for individuals and organizations. Many existing detection systems depend on traditional feature extraction methods or private datasets, which limit their effectiveness and reduce reproducibility in real-world applications. To overcome these challenges, this study proposes a hybrid text classification framework for phishing email detection by integrating TF-IDF, Word2Vec, and BERT-based contextual embeddings. This combined approach captures lexical importance, semantic relationships, and contextual meaning within email content. The model is trained and evaluated using a large publicly available phishing email dataset to ensure reliability and practical relevance. Experimental findings show that the proposed approach achieves an accuracy of 99.23%. The proposed model demonstrates improved performance compared to conventional single-feature models. The developed system provides a robust, scalable, and efficient solution for phishing email classification and supports the development of real-time applications for strengthening email security against evolving phishing attacks.

### Introduction:

The rapid growth of digital communication has made email one of the most important tools for personal and professional use. However, this growth has also increased the number of cyber threats, especially phishing attacks. Phishing is a type of cybercrime where attackers send fake emails that appear to come from trusted sources such as banks, companies, or service providers. The main goal is to trick users into sharing sensitive information such as passwords, banking details, or personal data. According to Phish Tank, there are 45 thousand phishing links [1].

Phishing attacks continue to increase worldwide and have become one of the most

dangerous cybersecurity problems. These attacks cause serious financial losses, data breaches, and damage to organizational security. Many phishing emails are carefully designed to look genuine which make them difficult for users to identify manually. According to the Phishing Threats Report [2], which analyzed more than 13 billion emails, phishing attacks are becoming increasingly sophisticated, with attackers frequently using deceptive links and identity impersonation techniques to exploit victims. As attackers continuously change their strategies, traditional rule-based detection systems are often unable to detect new phishing patterns effectively.

The critical need to address phishing is highlighted by its substantial financial consequences. According to the FBI, Business Email Compromise (BEC) attacks alone have resulted in global losses exceeding \$50 billion [3]. Furthermore, the 4th Quarterly Report of the Anti-Phishing Working Group (APWG) recorded more than 1,077,501 phishing attacks in the fourth quarter of 2023, with 15% of these attacks specifically targeting various webmail services [4]. To address this problem, Machine Learning (ML) and Natural Language Processing (NLP) techniques have become powerful solutions for phishing email detection. These methods can learn patterns from large datasets and automatically classify emails as phishing or legitimate. Compared to traditional detection methods, ML-based systems provide faster and more accurate results.

This research focuses on developing an effective phishing email classification system using a hybrid feature extraction approach. The proposed framework combines TF-IDF, Word2Vec, and BERT-based contextual embeddings to capture statistical, semantic, and contextual information from email content. By integrating these three techniques, the model can better understand the hidden patterns in phishing emails and improve classification accuracy. A large publicly available phishing email dataset is used for training and evaluation to ensure reliability and reproducibility.

The rest of this paper is organized as follows. Section 2 presents the related work and previous studies on phishing email detection. Section 3 explains the proposed methodology, including dataset collection, preprocessing, feature extraction, and model training. Section 4 discusses experimental results. Finally, Section 5 concludes the study and suggests possible future improvements.

## Literature Review:

The fast development of Artificial Intelligence (AI) tools has brought many benefits to daily life and business operations. However, this growth has also created new cybersecurity risks. Advanced AI tools can be used not only for helpful purposes but also by cybercriminals to create more convincing and sophisticated phishing attacks [5]. Attackers can now generate realistic phishing emails with better language quality and detecting them is more difficult for both users and traditional security systems.

Most recent research on phishing detection has mainly focused on identifying phishing websites through URL analysis [6-9], domain name checking [10], and website content inspection [11-14]. While these approaches are effective, phishing emails remain one of the most common entry points for cyberattacks and require stronger detection methods. Machine Learning (ML) and Natural Language Processing (NLP) have shown strong potential in solving this problem by analyzing email content and automatically classifying messages as phishing or legitimate.

Several studies have applied different machine learning models for phishing and spam email detection [15, 16]. Traditional algorithms such as Naive Bayes, Decision Trees, Random Forest, and Support Vector Machine (SVM) have produced strong results in many cases. Among these, SVM and Random Forest often show better performance due to their ability to handle complex text classification tasks. Deep learning methods such as Recurrent Neural Networks (RNN) [17], Convolutional Neural Networks (CNN) [18], Long Short-Term Memory (LSTM) [19], and transformer-based models like BERT [20] have also achieved very high accuracy in recent studies.

BERT-based models have become especially important because they can understand contextual meaning in text, which helps in detecting phishing emails more effectively than traditional feature extraction methods alone. Some studies using fine-tuned BERT models have reported accuracy above 98%, while hybrid deep learning approaches combining CNN, LSTM, and attention mechanisms have achieved even higher results. However, many of these studies rely on small datasets, private datasets, or limited benchmark collections, which reduces model generalizability and practical usability in real-world environments.

Other researchers have explored ensemble learning, graph-based models, and transformer-based architectures for phishing detection. Some studies also used optimization techniques such as Genetic Algorithms and Particle Swarm Optimization to improve feature selection and classification performance. Although these methods show strong results, many existing solutions focus mainly on model accuracy without considering large-scale public datasets or real-time deployment possibilities.

The literature review reveals two major limitations in current phishing email detection research. First, many studies depend on private or small datasets, making it difficult to reproduce results and test generalizability. Second, there is often a gap between high-performing research models and their practical implementation in real-world systems. This study aims to address these limitations by proposing a hybrid phishing email classification model using TF-IDF, Word2Vec, and BERT-based contextual embeddings. The combination of these three feature extraction techniques helps capture statistical importance, semantic relationships, and contextual meaning from email content more effectively than single-feature methods. The model is trained using a large publicly available phishing email dataset to improve reliability, robustness, and reproducibility.

## Objectives:

The main objectives of this research are:

To develop an effective phishing email classification system using a hybrid feature extraction approach.

To evaluate and compare the performance of multiple machine learning in detecting phishing emails accurately.

To improve the reliability and generalizability of phishing email detection by training and testing the model on a large publicly available dataset.

## Methodology:

The proposed system for phishing email classification follows a structured pipeline shown in Figure 1 that includes data collection, preprocessing, feature extraction,

model training, evaluation, and deployment. The main objective is to build a highly accurate and reliable model using hybrid feature representation based on TF-IDF, Word2Vec, and BERT [21] contextual embeddings.

To improve the robustness and generalizability of the model, multiple publicly available phishing and spam email datasets were selected and combined into a single unified dataset. Using multiple datasets helps the model learn different phishing patterns and reduces bias caused by relying on only one source.

After data collection, the text data was cleaned and preprocessed using Natural Language Processing (NLP) [22] techniques. This step included removing special characters, punctuation marks, unnecessary symbols, HTML tags, and duplicate records. All text was converted into lowercase to maintain consistency. Tokenization [23] was then applied to split the text into meaningful words or tokens. Stopwords such as “the,” “is,” and “and” were removed since they do not contribute significantly to classification. Lemmatization [24] was also performed to reduce words to their base form and improve text consistency.

To preserve the contextual meaning of each email, important textual fields such as sender information, subject, and email body were merged into a single column. This combined representation allows the model to better understand the full intent and structure of the email rather than analyzing separate fields independently.

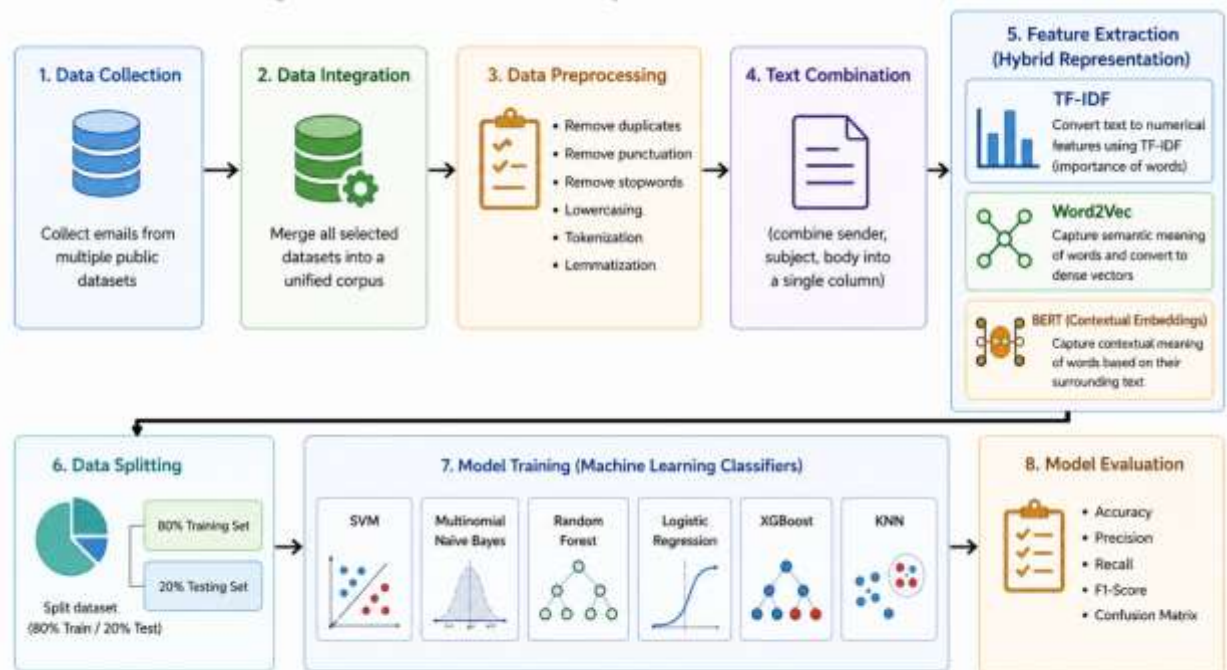


Figure 1: Proposed Methodology for Phishing Email Detection

## Datasets Description

A reliable phishing email detection system requires a diverse and well-structured dataset for effective training and evaluation. In this study, multiple publicly available email datasets were selected to improve the robustness and generalization ability of the proposed model. Each dataset contributes different characteristics of phishing,

spam, and legitimate (ham) emails. These datasets allow the model to learn a wider range of attack patterns and normal communication behavior. The summary of each dataset is included in Table 1.

The Enron Email Dataset [25] is one of the most widely used benchmark datasets for email classification research. It was extracted from the publicly available Enron email corpus and contains both phishing and legitimate emails. In this study, 15,791 legitimate emails and 13,976 phishing emails were used. Its large size and public availability make it highly useful for machine learning experiments. However, since the emails mainly originate from Enron employees, the dataset has limited diversity and may not fully represent modern phishing strategies.

The CEAS 2008 Spam Challenge Corpus [26] is another important dataset used in this research. It contains 39,154 email samples, including 17,312 legitimate emails and 21,842 spam emails. This dataset provides a broad range of spam patterns and is useful for improving model robustness. However, because it was collected during an earlier period, some phishing techniques may be outdated compared to current real-world attacks. In addition, accessibility is limited because usage may require special permission.

The Ling-Spam Corpus [27] is a publicly available collection of emails from the Linguist List forum. It contains 2,412 legitimate emails and 481 spam emails. This dataset is commonly used for benchmarking text classification models because of its clean structure and easy accessibility. However, its smaller size and domain-specific focus on linguistics reduce its generalization capability for broader phishing detection tasks.

The Nazario Spam Dataset [28] mainly focuses on phishing emails and is useful for evaluating phishing-specific detection models. A subset of this dataset obtained from Zenodo was used in this study. Its main advantage is that it provides direct examples of phishing attacks, helping the model learn phishing patterns more effectively. However, the exact source of the data is not always clearly documented, which may introduce bias and reduce reliability.

The Nigerian Fraud Dataset [29] focuses on advance-fee fraud emails, commonly known as scam emails. A subset of this dataset from Zenodo was included in this research. It provides useful examples of financial fraud attempts and helps improve the model's ability to detect scam-related phishing attacks. However, the dataset is relatively small and less commonly available compared to standard spam datasets.

The SpamAssassin Public Corpus [30] is a well-known freely available dataset maintained by the Apache Software Foundation. In this research, 4,091 legitimate emails and 1,718 spam emails were used. Its clear labeling and public accessibility make it useful for model evaluation and comparison. However, the dataset is smaller than some other datasets and may contain older spam patterns that do not fully reflect modern phishing attacks.

Although each dataset has its own limitations, combining them creates a more comprehensive and balanced dataset. This integration reduces the weaknesses of individual datasets and improves the model's ability to generalize across different phishing styles and email structures. By merging these datasets, the proposed phishing email classification system becomes more reliable, robust, and suitable for real-world deployment.

Table 1: Summary of Email Datasets Used

| Dataset Name           | Source              | Samples Used                | Strengths                             | Limitations                                   |
|------------------------|---------------------|-----------------------------|---------------------------------------|-----------------------------------------------|
| Enron Email Dataset    | Public Enron Corpus | 15,791 ham +13,976 phishing | Large size, publicly available        | Limited diversity, focused on Enron employees |
| CEAS 2008 Spam Corpus  | CEAS Spam Challenge | 17,312 ham +21,842 spam     | Diverse spam patterns, large dataset  | Older phishing tactics, limited accessibility |
| Ling-Spam Corpus       | Linguist List Forum | 2,412 ham + 481 spam        | Easy access, common benchmark dataset | Small size, domain-specific focus             |
| Nazario Spam Dataset   | Zenodo Subset       | Phishing-focused subset     | Strong phishing examples              | Unclear data origin, possible bias            |
| Nigerian Fraud Dataset | Zenodo Subset       | Scam-focused subset         | Useful for fraud detection            | Small size, limited availability              |
| SpamAssassin Corpus    | Apache Foundation   | 4,091 ham + 1,718 spam      | Pre-labeled, publicly available       | Smaller size, older spam patterns             |

## Data pre-processing:

Data preprocessing is an important step in phishing email classification because raw email data often contains unnecessary information, noise, and inconsistencies that can negatively affect model performance. Before feature extraction and model training, the collected email datasets were carefully cleaned and standardized using several Natural Language Processing (NLP) [22] techniques to improve data quality and classification accuracy.

The first step involved removing duplicate records from the merged dataset. Duplicate emails can create bias during model training and may lead to misleading evaluation results. Eliminating repeated samples [31] helps ensure that the model learns meaningful patterns rather than memorizing identical records. Next, punctuation marks, special symbols, unnecessary characters, HTML tags, and irrelevant formatting elements were removed from the email content [32]. These elements usually do not contribute useful information for phishing detection and may increase noise in the dataset. Cleaning text helps simplify the content and improves feature extraction.

All text was then converted into lowercase format to maintain consistency across the dataset. For example, words such as “Account,” “ACCOUNT,” and “account” were treated as the same word after lowercasing. This reduces feature duplication and improves the efficiency of text representation methods. Stopword removal [33] was also applied to eliminate commonly used words such as “the,” “is,” “and,” and “was,” which usually carry little meaning for classification tasks. Removing these words

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helps the model focus on more informative terms such as “verify,” “account,” “urgent,” and “payment,” which are more relevant for identifying phishing emails. Tokenization [23] was performed to split the cleaned text into smaller meaningful units called tokens, usually individual words. This process helps prepare the text for vectorization techniques such as TF-IDF, Word2Vec, and BERT by converting unstructured text into a form suitable for machine learning analysis. Finally, lemmatization [24] was applied to reduce words to their base or root form. For example, words like “verifying,” “verified,” and “verification” are reduced to the root word “verify.” This improves consistency and helps the model better understand similar words with the same meaning.

After completing these preprocessing steps, the cleaned and standardized text was ready for feature extraction and hybrid vector representation. Proper preprocessing significantly improves model performance by reducing noise and ensuring better quality input for phishing email classification.

### **Text Combination:**

In phishing email detection, important information is often distributed across multiple fields such as sender details, subject line, and email body. Analyzing these fields separately may reduce the model’s ability to understand the complete context of an email. To improve classification performance, a text combination step was performed by merging these important textual features into a single column.

For datasets containing only subject and body fields, both columns were combined into one column. For datasets that included additional fields such as sender information, subject, and body content, all these fields were merged into the same column. This approach helps preserve the overall meaning and structure of the email by allowing the model to analyze the full message as a single text instance. Combining multiple fields into one column improves contextual understanding because phishing indicators may appear in different parts of an email. For example, suspicious sender addresses, urgent subject lines, and deceptive message content together provide stronger evidence of phishing than any single field alone. By integrating all relevant textual information, the model can better capture hidden relationships and improve detection accuracy.

This combined text representation also simplifies the preprocessing and feature extraction stages. Instead of handling multiple columns separately, the machine learning pipeline processes one standardized text column, making vectorization more efficient and consistent across all datasets. The final column served as the main input for feature extraction techniques including TF-IDF, Word2Vec, and BERT-based contextual embeddings, supporting the development of a more accurate and robust phishing email classification model.

### **Feature Extraction:**

Since machine learning algorithms require numerical input, the textual data was transformed into vector representations using three feature extraction techniques:

## TF-IDF (Term Frequency–Inverse Document Frequency)

TF-IDF [34] measures the importance of a word in a document compared to the entire dataset, represented using equation 1. Words that appear frequently in one email but less frequently across all emails receive higher importance scores. This helps identify suspicious words commonly used in phishing emails such as “verify,” “urgent,” or “account.”

$$TF - IDF(w, d) = TF(w, d) \times IDF(w, D) \dots \dots \dots (1)$$

Where,  $TF(w, d)$  is calculated as the number of times word  $w$  appears in document  $d$  divided by the total number of words in document  $d$ .  $IDF(w, D)$  is calculated using the logarithm of the total number of documents in the corpus ( $D$ ) divided by the number of documents containing word  $w$  ( $df(w)$ ).

## Word2Vec

Word2Vec [35] is used to capture semantic relationships between words by converting them into dense vector representations. Unlike TF-IDF, Word2Vec helps the model understand the similarity between words based on context. For example, words like “bank” and “payment” may appear close in vector space if they are used in similar contexts [46].

## BERT-Based Contextual Embeddings

BERT (Bidirectional Encoder Representations from Transformers) [20, 21] was used to capture contextual meaning within email content. Unlike traditional embedding techniques such as TF-IDF and Word2Vec, which mainly focus on word frequency and fixed semantic relationships, BERT understands the meaning of a word based on the surrounding words in a sentence. This bidirectional learning allows the model to analyze both the left and right context of a word simultaneously.

This is important in phishing email detection because phishing messages often use carefully crafted language that appears legitimate but contains hidden malicious intent. For example, words such as “verify,” “update,” or “secure” may have different meanings depending on the sentence context. Traditional methods may fail to distinguish these subtle differences, while BERT can better capture such contextual patterns and identify suspicious language more accurately.

While TF-IDF captures statistical importance and Word2Vec captures semantic similarity, BERT adds contextual intelligence by understanding how words are used within the full email content. This combination creates a stronger hybrid feature representation for phishing email classification.

The use of BERT significantly improves the model’s ability to detect complex phishing attempts that rely on social engineering and deceptive writing styles rather than obvious spam keywords. By integrating BERT with TF-IDF and Word2Vec, the proposed system achieves higher classification accuracy and stronger generalization compared to traditional single-feature approaches.

The final hybrid feature representation combines all three techniques:

$$F = TF-IDF + Word2Vec + BERT$$

## Classification

Several machine learning classifiers were implemented and compared to identify the best-performing model for phishing email detection.

## Support Vector Machine (SVM)

Support Vector Machine is highly effective for text classification problems. It works by finding the optimal hyperplane that separates phishing and legitimate emails with maximum margin. A linear kernel was used for efficient performance on high-dimensional text data.

## Multinomial Naïve Bayes (MNB)

Multinomial Naïve Bayes is a probabilistic classifier commonly used for text classification. It performs well with word frequency-based features such as TF-IDF and offers fast training and prediction.

## Random Forest Classifier

Random Forest is an ensemble learning method that uses multiple decision trees to improve classification accuracy and reduce overfitting. Each tree makes an independent prediction, and the final result is based on majority voting.

## Logistic Regression

Logistic Regression is a simple yet powerful classifier for binary classification tasks. It performs efficiently on large text datasets and provides strong baseline performance for phishing detection.

## XGBoost Classifier

XGBoost is a powerful gradient boosting algorithm known for high accuracy and strong performance in classification tasks. It helps capture complex patterns in phishing emails and improves predictive capability.

## K-Nearest Neighbors (KNN)

KNN classifies emails based on similarity to nearby training samples. Although computationally heavier for large datasets, it helps evaluate how well phishing emails cluster in feature space.

## Results and Discussion:

This section presents the experimental results of the proposed phishing email classification framework and compares its performance on traditional machine learning models and existing state-of-the-art studies. The evaluation is carried out using multiple performance metrics including Accuracy, Precision, Recall, F1-Score, and AUC-ROC to ensure a comprehensive assessment of model effectiveness.

The results of different machine learning classifiers are summarized in Table 2. Among all tested models, the Support Vector Machine (SVM) achieved the best overall performance with an accuracy of 99.23%, precision of 99.14%, recall of 98.76%, F1-score of 99.43%, and AUC-ROC of 99.21%. This indicates that SVM is highly effective in distinguishing between phishing and legitimate emails when

trained on the proposed hybrid feature representation.

Multinomial Naïve Bayes also performed competitively with an accuracy of 98.78%, showing strong consistency across all evaluation metrics. However, it slightly underperformed compared to SVM, particularly in F1-score and AUC-ROC, indicating that probabilistic assumptions may limit its performance in complex feature spaces.

Ensemble-based and linear models such as Random Forest, Logistic Regression, and XGBoost showed moderate performance, with accuracies ranging from 96.76% to 97.91%. Although these models are robust, they did not outperform SVM or Naïve Bayes in this experimental setup. K-Nearest Neighbors (KNN) recorded the lowest performance among all classifiers, achieving an accuracy of 96.13%, which suggests that distance-based methods are less effective for high-dimensional text data.

Table 2. Performance of Machine Learning Models

| Model                   | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) | AUC   |
|-------------------------|--------------|---------------|------------|--------------|-------|
| SVM                     | 99.23        | 99.14         | 98.76      | 99.43        | 99.21 |
| Multinomial Naïve Bayes | 98.78        | 98.81         | 98.83      | 98.79        | 98.81 |
| Random Forest           | 97.91        | 97.93         | 97.93      | 97.92        | 97.91 |
| Logistic Regression     | 97.31        | 97.34         | 97.33      | 97.31        | 97.31 |
| XGBoost                 | 96.76        | 96.74         | 96.76      | 96.76        | 96.75 |
| KNN                     | 96.13        | 96.12         | 96.13      | 96.13        | 96.13 |

To evaluate the effectiveness of the proposed approach, a comparison with recent state-of-the-art studies is presented in Table 3. The results show that the proposed model achieves competitive and, in some cases, superior performance compared to existing research.

For instance, Mohammad et al. reported an accuracy of 95.80%, while Gholampour et al. achieved 94.00%, which are significantly lower than the proposed model. Jamal et al. reported a high accuracy of 98.99%, but without complete metric evaluation such as precision, recall, or F1-score. More recent deep learning-based studies such as Al Tawil et al. and Alsubaie et al. achieved very high accuracies of around 99% and 99.51%, respectively. Although these results are slightly higher in some cases, they often rely on specific datasets or deep learning architectures without detailed multi-model comparison.

The proposed model achieves an accuracy of 99.23%, with strong precision, recall, and F1-score values (99.14%, 98.76%, and 99.43% respectively) along with an AUC-ROC of 99.21%. This indicates that the model not only performs well in classification accuracy but also maintains a strong balance between correctly identifying phishing emails and minimizing false predictions.

Table 3. Comparison of the Proposed Model with Existing Studies

| Study                    | Accuracy (%) | Precision (%) | Recall (%)   | F1-Score (%) | AUC          |
|--------------------------|--------------|---------------|--------------|--------------|--------------|
| Gholampour et al. [36]   | 94.00        | -             | -            | -            | -            |
| Mohammad et al. [37]     | 95.80        | 94.40         | 95.80        | 95.10        | -            |
| Jamal et al. [38]        | 98.99        | -             | -            | -            | -            |
| Al Tawil et al. [39]     | 99.00        | 99.00         | 99.00        | 99.00        | -            |
| Alsubaie et al. [40]     | 99.51        | 99.50         | 99.68        | 99.52        | -            |
| Uddin & Sarker [41]      | 99.00        | -             | -            | -            | -            |
| MeAJOR Corpus Study [42] | -            | -             | -            | 98.34        | -            |
| <b>Proposed Model</b>    | <b>99.23</b> | <b>99.14</b>  | <b>98.76</b> | <b>99.43</b> | <b>99.21</b> |

The experimental results clearly demonstrate that the hybrid feature representation approach (TF-IDF, Word2Vec, and BERT embeddings) significantly improves phishing email classification performance. The high performance of SVM suggests that when combined with rich feature representations, traditional machine learning models can still outperform more complex approaches in certain scenarios.

Compared to existing studies shown in Table 3, the proposed method provides a balanced improvement across all evaluation metrics rather than focusing only on accuracy. This makes the model more reliable for real-world deployment, where false positives and false negatives can have serious consequences.

Furthermore, the use of a large and diverse dataset contributes to improved generalization, reducing the risk of overfitting that is often observed in studies using smaller or domain-specific datasets. Overall, the results confirm that the proposed system is both effective and practical for real-time phishing email detection applications.

## Limitations:

Although the proposed phishing email classification model achieves high performance, there are still a few limitations. First, the model depends on publicly available datasets, which, although diverse, may not fully represent the latest and most sophisticated phishing techniques used in real-world attacks. Phishing strategies continuously evolve, and new attack patterns may not be fully captured in the training data. Second, the hybrid feature extraction approach combining TF-IDF, Word2Vec, and BERT increases computational complexity. It requires higher processing time and memory compared to simpler models, which may affect scalability in low-resource environments. Lastly, although the model performs well on test data, real-world deployment may introduce challenges such as noisy inputs, multilingual emails, and adversarially crafted phishing messages, which could slightly affect performance.

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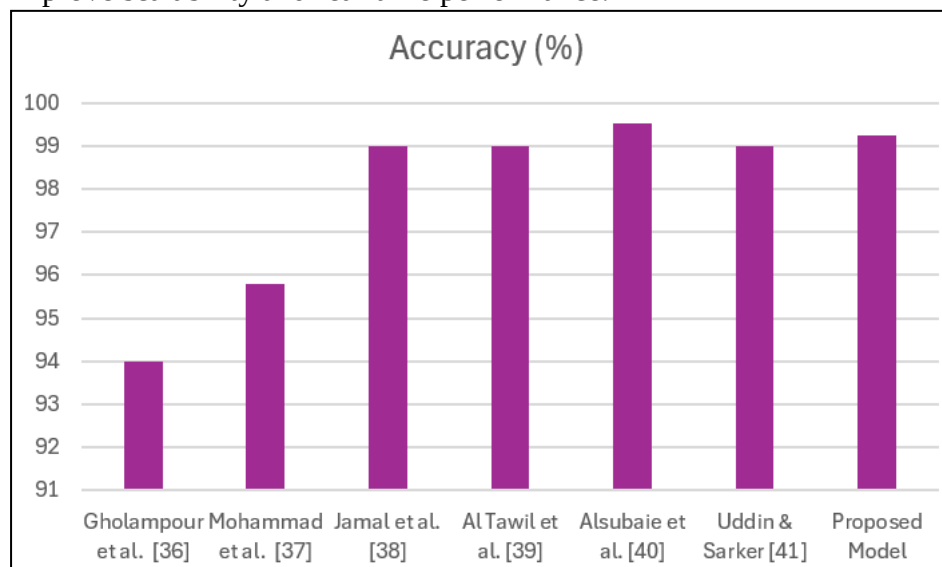
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## Conclusion:

This study proposed an effective phishing email classification system based on a hybrid feature extraction approach combining TF-IDF, Word2Vec, and BERT contextual embeddings. The integration of statistical, semantic, and contextual representations enabled the model to capture complex patterns in email content more effectively than traditional single-feature methods. Multiple machine learning classifiers were evaluated, and the Support Vector Machine (SVM) achieved the best performance with an accuracy of 99.23%. The results confirm that combining diverse feature representations significantly improves phishing email detection accuracy and reliability. Overall, the developed system provides a robust and practical solution for identifying phishing emails and can support real-time cybersecurity applications. For future work, the model can be further improved by incorporating advanced transformer-based architectures such as fine-tuned BERT variants or domain-specific language models trained specifically on cybersecurity text. Additionally, deploying the system in large-scale cloud environments and optimizing it for faster inference can improve scalability and real-time performance.



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