A Hybrid Structural and TF-IDF-based Machine Learning Framework for Large-Scale Phishing URL Detection

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ABSTRACT
Phishing attacks continue to pose significant cybersecurity risks by exploiting deceptive URLs to obtain sensitive user information, thereby necessitating accurate and scalable automated detection mechanisms. This study proposes a machine learning–based approach for phishing URL classification by integrating structural URL feature extraction with Natural Language Processing (NLP) techniques using Term Frequency–Inverse Document Frequency (TF-IDF). The dataset comprises 822,010 labeled URLs, consisting of 52% legitimate and 48% phishing instances, with prior validation to ensure the absence of missing values. Feature engineering was conducted through two complementary strategies: handcrafted structural features—including URL length, domain length, number of digits, special characters, suspicious keywords, HTTPS usage, and number of subdomains and TF-IDF based textual representation using unigram, bigram, and trigram tokenization. The combined feature set was used to train a Random Forest classifier with optimized hyperparameters, and model evaluation was performed using Stratified 5-Fold Cross Validation to preserve class distribution across training and testing subsets. Performance assessment was conducted using confusion matrix, precision, recall, and F1-score to provide a comprehensive evaluation of detection capability. The experimental findings indicate that the integration of structural and textual features significantly improves classification effectiveness, enabling robust and balanced detection of phishing and legitimate URLs, thus demonstrating the practical applicability of the proposed method for large-scale real-world deployment.

General Terms
Cybersecurity, Web Security, Machine Learning, Natural Language Processing, Classification Systems

Keywords
Phishing URL Detection, Random Forest, TF-IDF, URL Feature Extraction, Stratified K-Fold Cross Validation, Ensemble Learning

1. INTRODUCTION
Phishing continues to represent one of the most persistent and financially damaging cybersecurity threats worldwide, targeting individuals and organizations through deceptive digital communication techniques [1]. Attackers typically impersonate trusted entities and embed malicious Uniform Resource Locators (URLs) within emails, instant messages, or social media platforms to redirect victims to fraudulent websites designed to harvest sensitive information such as login credentials, financial records, or personal data [2]. Recent empirical studies indicate that phishing campaigns have become increasingly sophisticated, employing dynamically generated URLs and domain spoofing techniques to evade traditional detection mechanisms [3].

Conventional phishing mitigation strategies rely heavily on blacklist-based filtering, rule-based heuristics, and signature detection systems [4]. However, these approaches are inherently reactive and struggle to detect zero-day phishing URLs that have not yet been cataloged in threat databases [5]. Moreover, static rule-based systems often fail when attackers introduce slight lexical or structural modifications to URLs, such as obfuscation, character substitution, or subdomain manipulation [6]. As a result, automated phishing detection using Machine Learning (ML) and Natural Language Processing (NLP) has emerged as a promising alternative capable of learning discriminative patterns directly from data [7]. Recent literature highlights the effectiveness of ML-based phishing detection models that analyze structural and lexical features extracted from URLs [8]. Ensemble learning algorithms, particularly Random Forest, have demonstrated strong classification capability due to their robustness against noisy features and ability to reduce overfitting through decision tree aggregation [9]. Comparative studies evaluating multiple ML algorithms confirm that Random Forest frequently outperforms single classifiers such as Decision Trees and Support Vector Machines in phishing URL detection tasks [10].

Beyond classical ML, deep learning techniques have gained substantial attention. Convolutional Neural Networks (CNNs) have been successfully applied to learn hierarchical character-level representations of URLs, achieving high classification accuracy in large-scale datasets [11]. Similarly, recurrent neural architectures such as Long Short-Term Memory (LSTM) and Bidirectional LSTM networks have demonstrated the capacity to capture sequential dependencies within URL strings, improving generalization across diverse phishing patterns [12]. Hybrid deep learning frameworks combining CNN and ensemble methods have further enhanced detection robustness while reducing false positive rates [13]. Parallel to advances in deep architectures, NLP-based feature engineering remains a powerful and computationally efficient approach for phishing detection. Techniques such as Term Frequency–Inverse Document Frequency (TF-IDF) transform textual URL components into weighted numerical representations that emphasize discriminative tokens [14]. Comparative analyses of TF-IDF, Word2Vec, and transformer-based embeddings indicate that textual representation plays a critical role in distinguishing phishing URLs from legitimate ones [15]. Transformer-based models such as BERT have demonstrated improved semantic understanding in phishing-related classification tasks; however, they often require extensive computational resources for training and inference [16].

Despite these advances, several research challenges remain. First, deep learning approaches, while accurate, often require

high computational overhead and large labeled datasets, limiting real-time deployment feasibility in resource-constrained environments [17]. Second, many studies focus either on structural URL features or on textual embeddings independently, without systematically integrating both feature categories into a unified and interpretable classification framework [18]. Third, rigorous evaluation strategies such as Stratified K-Fold Cross Validation are not consistently applied across studies, potentially leading to biased performance estimation, particularly in imbalanced phishing datasets [19]. Furthermore, the evolving nature of phishing tactics, including the use of adversarially generated domains and AI-assisted phishing content, necessitates adaptable and generalizable detection pipelines [20].

To address these limitations, this research proposes an integrated phishing URL detection framework that combines structural URL feature engineering with NLP-based TF-IDF representation and employs the Random Forest algorithm for classification. The proposed approach begins with preprocessing to ensure dataset integrity and balanced class distribution. Structural features such as URL length, domain depth, number of subdomains, suspicious tokens, and special character counts are extracted and combined with TF-IDF-based textual representations of URL strings. The dataset is partitioned using Stratified K-Fold Cross Validation to preserve class proportions across training and testing subsets, ensuring robust and unbiased evaluation [21]. The Random Forest classifier is selected due to its demonstrated effectiveness in phishing detection, interpretability through feature importance analysis, and resilience to high-dimensional feature spaces [22]. Model performance is evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis, providing comprehensive insight into detection effectiveness. This study makes three primary contributions. First, it develops a structured and reproducible NLP-driven feature engineering pipeline tailored for phishing URL detection. Second, it empirically demonstrates that combining TF-IDF representations with structural URL attributes enhances classification robustness while maintaining computational efficiency. Third, it provides systematic validation using stratified cross-validation on a large labeled dataset, contributing practical insights for real-world deployment of phishing detection systems.

2. RESEARCH METHOD

This study employs a systematic machine learning framework to develop a phishing URL detection system based on structural and textual feature analysis. As illustrated in Fig. 1, the research consists of several sequential stages, including dataset preparation, data preprocessing, feature extraction, dataset partitioning using stratified validation, model construction with an ensemble classifier, and performance evaluation using standard classification metrics. Each stage is designed to ensure methodological rigor, reproducibility, and objective performance assessment. The detailed technical procedures and theoretical foundations of each stage are elaborated in the following subsections.

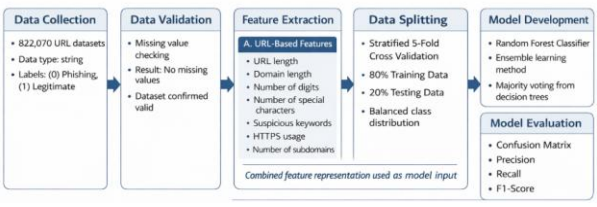

Fig 1: Phising URL Classification Research Methodology

2.1 URL Dataset

The dataset used in this study consists of 822,010 URL instances collected from publicly available cybersecurity repositories and phishing monitoring platforms. Each URL is labeled into two categories: phishing (0) and legitimate (1). Large-scale labeled datasets are essential in phishing detection research because model performance is highly dependent on data diversity and representativeness, particularly when addressing evolving attack patterns and domain obfuscation techniques [23]. Recent studies emphasize that balanced binary datasets improve classifier generalization and reduce bias during supervised learning [24].

The dataset contains two primary attributes: url**,** which stores the web address in string format, and status**,** which represents the binary classification label. No additional handcrafted attributes are provided in the raw dataset. This raw-text format allows feature engineering processes to extract structural and lexical characteristics directly from URL strings, a strategy commonly adopted in modern URL-based phishing detection systems [25]. Lexical analysis of URL strings has been demonstrated to be highly effective because phishing URLs often exhibit distinguishable patterns, such as abnormal length, suspicious keywords, or irregular domain structures [26].

In terms of distribution, approximately 52% of the dataset consists of legitimate URLs, while 48% are phishing URLs. Maintaining a relatively balanced distribution is important to prevent model bias toward the majority class and to ensure stable performance evaluation [27]. Imbalanced datasets in cybersecurity classification tasks may lead to inflated accuracy while failing to correctly detect malicious samples, particularly when phishing instances are underrepresented [28]. Table 1 presents sample entries from the dataset used in this study.

Table 1. Sample URL Dataset

URL	Status
http://example.com/*login*	1
http://secure-update-account.com/verify	0
https://www.bankofamerica.com/security-update	1
http://paypal-*login*.com/secure	0

2.2 Missing Value Detection

The initial stage of data preprocessing involves inspecting the dataset for missing values that may compromise model reliability. Missing or null entries can occur due to data collection inconsistencies, transmission errors, or formatting issues during dataset aggregation. In machine learning pipelines, particularly in cybersecurity applications, incomplete data may lead to biased model learning, unstable convergence, or inaccurate predictions [34]. Therefore, ensuring dataset integrity before feature extraction is considered a fundamental step in robust phishing detection systems.

The dataset used in this study contains two attributes: url, which stores URL strings, and status, which represents binary class labels (0 for phishing and 1 for legitimate). A systematic inspection was conducted to detect null values across both attributes. Handling missing values is especially critical in text-based classification problems, as corrupted string inputs may disrupt tokenization processes and distort feature vector representations [35]. Studies in secure machine learning emphasize that preprocessing quality directly influences downstream feature engineering effectiveness and classifier

performance [36].

The inspection process was implemented using the isna().sum() function to calculate the total number of missing values per column. Subsequently, dropna(inplace=True) was applied to remove any incomplete entries from the dataset. Although no missing values were detected in this dataset after inspection, explicitly performing this validation step ensures methodological transparency and reproducibility. Recent research highlights that clearly documented preprocessing procedures enhance experimental credibility and reduce risks of hidden data leakage in cybersecurity classification studies [37].

Fig 2 illustrates the missing value inspection process applied in this study.

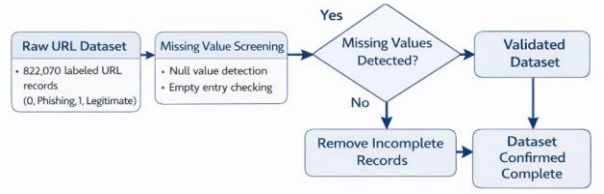

Fig 2: Missing Value Detection Process

2.3 Feature Extraction

Feature extraction is a critical stage in phishing URL detection, as raw URL strings must be transformed into numerical representations before being processed by machine learning algorithms. This study employs a dual-feature extraction strategy consisting of structural URL-based features and text-based TF-IDF representations. Combining multiple feature perspectives has been shown to improve classification robustness by capturing both lexical irregularities and contextual token patterns within malicious URLs [31], [32].

2.3.1 Structural URL Feature Extraction

The first approach focuses on extracting handcrafted structural features derived directly from URL components. Structural analysis is widely adopted in phishing detection research because malicious URLs often exhibit measurable anomalies in lexical composition and domain structure [26], [33]. These anomalies typically arise from obfuscation techniques, social engineering cues, and brand impersonation strategies. The feature extraction process is implemented through a custom function that converts each URL into a numerical feature vector. The extracted features include URL length, domain length, number of digits, number of special characters, presence of suspicious keywords, HTTPS usage indicator, and number of subdomains.

URL length is calculated as the total number of characters in the URL string. Phishing URLs tend to be longer due to appended deceptive paths or encoded parameters intended to obscure the actual domain [32]. Domain length is extracted using domain parsing techniques to isolate the primary domain name. Abnormally long or manipulated domain names are often associated with phishing attacks [30]. The number of digits within the URL is computed to detect numerical obfuscation, which is frequently used to imitate account identifiers or transactional references. Similarly, the number of special characters (such as '-', '@', '=', '&') is measured, as excessive punctuation is often employed to create misleading URL structures [33]. A binary feature is used to indicate the presence of suspicious keywords, including "secure," "account," "login," "banking," "confirm," "verify," and "update." Prior empirical findings suggest that such tokens are frequently embedded within phishing URLs to induce urgency and credibility perception [29]. Another binary feature identifies whether the URL uses HTTPS. While HTTPS does not guarantee legitimacy, the absence of HTTPS is often correlated with malicious intent in large-scale phishing datasets [32]. Finally, the number of subdomains is computed by analyzing the subdomain structure. Phishing URLs frequently employ deep subdomain hierarchies to mimic legitimate domains and mislead users [30, 33]. These structural indicators collectively form a compact yet discriminative numerical representation of each URL.

2.3.2 TF-IDF Text-Based Feature Extraction

In addition to structural features, this study applies a TF-IDF (Term Frequency–Inverse Document Frequency) transformation to capture textual patterns embedded within URLs. Treating URLs as textual documents enables the model to identify distinctive token distributions associated with phishing campaigns [31]. The TF-IDF vectorizer is configured with a maximum of 5,000 features and an n-gram range of (1,3), incorporating unigram, bigram, and trigram representations. The inclusion of higher-order n-grams allows the model to capture sequential token dependencies, which significantly enhances phishing detection performance compared to unigram-only approaches [36].

During tokenization, each URL is decomposed into overlapping token sequences. The TF component measures the frequency of each token within a URL, while the IDF component reduces the weight of tokens that are common across many URLs. Consequently, rare yet highly indicative tokens—such as "verify-account" or "secure-login-update"—receive higher discriminative weight. This weighting mechanism improves the classifier's sensitivity to subtle phishing patterns while suppressing noise from ubiquitous tokens such as "com" [35].

The final output of this process is a sparse high-dimensional matrix in which each row represents a URL and each column corresponds to a weighted n-gram feature. The structural and TF-IDF features are subsequently concatenated to form a unified feature matrix. Hybrid feature integration has been shown to outperform single-representation approaches by leveraging complementary lexical and contextual information [31, 37].

2.4 Dataset Partitioning

After feature construction, the complete feature matrix is partitioned into training and testing subsets to ensure objective and unbiased performance evaluation. In this study, Stratified K-Fold Cross-Validation with five folds is employed to maintain proportional class distribution across all partitions. Stratified validation has been widely recommended in cybersecurity classification research because it preserves class balance and reduces sampling bias during model evaluation [38].

The dataset consists of 822,010 labeled URL instances. By applying five-fold cross-validation, the dataset is divided into five equally sized subsets, each containing 164,402 URLs. In every iteration, four folds (80%) are used for training, while one fold (20%) is reserved for testing. This configuration results in 657,608 URLs for training and 164,402 URLs for testing per iteration. Cross-validation has been shown to provide a more reliable estimation of model generalization performance compared to single hold-out validation, particularly in large-scale classification problems [39].

Stratification ensures that the original class distribution—52% legitimate and 48% phishing—is preserved within each fold. Maintaining proportional representation is critical in phishing detection tasks because skewed class distributions may lead to biased learning behavior and misleading performance metrics [40]. Studies indicate that even moderately imbalanced datasets can distort recall and precision measurements if not properly controlled during partitioning [41]. Another advantage of K-Fold Cross-Validation is its ability to reduce performance variance by ensuring that each data instance is used both for training and testing across different iterations. This approach enhances experimental robustness and minimizes the risk of overestimating classifier performance [42]. Furthermore, repeated exposure to varied training subsets allows ensemble-based classifiers to better capture complex decision boundaries in high-dimensional feature spaces [43]. The partitioning process is implemented using the StratifiedKFold function from the Scikit-learn library with n_splits=5, shuffle=True, and random_state=42. The shuffle mechanism randomizes data order before splitting, while the fixed random state ensures experimental reproducibility.

2.5 Phishing Classification Model Construction

The core component of the proposed system is the construction of a phishing URL classification model using the Random Forest algorithm. Random Forest is an ensemble learning technique that combines multiple decision trees to improve predictive stability and reduce variance. Ensemble-based classifiers have been widely adopted in cybersecurity applications due to their robustness in handling noisy and high-dimensional feature spaces [44].

Random Forest operates by generating multiple decision trees using bootstrapped subsets of the training data and randomly selected feature subsets at each split. The final prediction is determined through majority voting among individual trees. This aggregation mechanism reduces overfitting and enhances generalization performance compared to single decision tree models [45]. In phishing detection tasks, where URL patterns can be highly heterogeneous and nonlinear, ensemble methods have demonstrated superior classification accuracy and stability [46].

The model in this study is configured with the following parameters:

- n_estimators = 200, specifying the number of decision trees;
- max_depth = 50, limiting tree depth to control model complexity;
- min_samples_split = 5, defining the minimum samples required to split an internal node;
- min_samples_leaf = 2, ensuring minimum samples at each leaf node;
- random_state = 42, for reproducibility;
- n_jobs = -1, enabling parallel processing across available CPU cores.

Limiting tree depth and minimum split size is important to mitigate overfitting, especially when training on high-dimensional TF-IDF feature matrices [47]. Sparse vector representations generated from n-gram TF-IDF can significantly increase dimensionality, and Random Forest has been shown to effectively manage such feature spaces without requiring extensive dimensionality reduction [48]. Model training is conducted iteratively within the Stratified 5-Fold Cross-Validation framework described previously. In each fold, the classifier is trained using 80% of the data and evaluated on the remaining 20%. Repeated training across folds enhances model robustness by exposing it to varying data distributions while maintaining class proportionality [49]. The ensemble voting mechanism allows the model to capture complex decision boundaries formed by the integration of structural and textual features. Hybrid feature-based ensemble classifiers have consistently demonstrated improved detection capability in phishing URL classification compared to single-feature or single-classifier approaches [50]. Fig 3 illustrates the conceptual workflow of the classification process using Stratified K-Fold Cross-Validation and the Random Forest ensemble model.

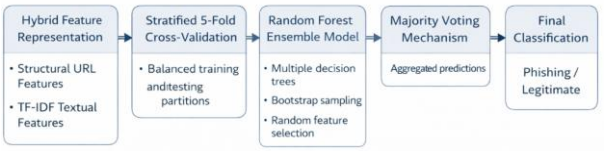

Fig 3: Conceptual Framework of Random Forest Based Phising URL Classification

2.6 Performance Evaluation

Model performance is evaluated using confusion matrix, precision, recall, and F1-score to provide a comprehensive assessment beyond overall accuracy, which can be misleading in binary cybersecurity classification tasks [51]. The confusion matrix quantifies True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) predictions, enabling detailed analysis of classification errors, particularly false negatives that may allow phishing URLs to bypass detection mechanisms [53]. Precision measures the proportion of correctly predicted phishing URLs among all predicted phishing instances, reflecting the model's ability to minimize false alarms [54], while recall evaluates the proportion of correctly detected phishing URLs among all actual phishing cases, which is critical for security-sensitive systems [55]. The F1-score, defined as the harmonic mean of precision and recall, provides a balanced performance indicator when trade-offs exist between detection sensitivity and false positive rates [56]. All evaluation metrics are averaged across the five folds of Stratified Cross-Validation to ensure stable and reliable generalization estimates [57].

3. RESULT AND DISCUSSION

This section presents a comprehensive evaluation of the proposed phishing URL detection system based on the Random Forest algorithm integrated with Natural Language Processing (NLP) techniques. The analysis covers dataset characteristics, feature extraction behavior, TF-IDF representation properties, model training using Stratified K-Fold Cross Validation, and an in-depth performance evaluation using standard classification metrics.

3.1 Dataset Description

The dataset used in this study consists of 822,010 labeled URLs, categorized into phishing (label 0) and legitimate (label 1). The data were stored in CSV format with two attributes: *url* (string) and *status* (integer). Initial validation confirmed that the dataset contained no missing or null values, ensuring structural consistency and eliminating the need for imputation. A preliminary statistical inspection revealed notable differences between the two classes. Phishing URLs tend to exhibit longer average character length, higher variability in domain structure, and more frequent usage of numeric and special characters. In contrast, legitimate URLs generally

follow standardized naming conventions, often associated with recognized domains and stable organizational structures. Further exploratory sampling indicates that phishing URLs frequently utilize obfuscation strategies, such as excessive subdomain nesting and dynamically generated paths. These observations highlight the importance of combining structural and lexical feature representations, as relying on a single feature type may fail to capture the full complexity of phishing patterns.

3.2 Data Preprocessing and Feature Extraction

Feature extraction was performed using a rule-based structural analysis approach, transforming each URL into seven numerical features. These features include URL length, domain length, number of digits, number of special characters, HTTPS usage, and subdomain count. Quantitative analysis shows that phishing URLs have: Higher mean URL length, Greater number of digits and special characters, and More complex subdomain structures

However, these features exhibit overlapping distributions between phishing and legitimate classes, indicating that no single feature can serve as a strong discriminator. For example, while phishing URLs often include keywords such as "login" or "secure," such terms also appear in legitimate authentication portals. Additionally, the increasing adoption of HTTPS by phishing websites reduces its effectiveness as a standalone indicator. These findings justify the integration of textual features (TF-IDF) with structural attributes to improve classification performance.

3.3 TF-IDF Representation

To capture lexical patterns, TF-IDF vectorization was applied with a maximum of 5,000 features and an n-gram range of (1,3). This resulted in a feature matrix of size 822,010 × 5,000. The TF-IDF matrix exhibited a high sparsity level of 99.89%, which is typical in text mining applications. Despite this sparsity, the representation effectively captures discriminative tokens. Vocabulary analysis revealed:

- Average token length: 9.21 characters
- Minimum token length: 2 characters
- Maximum token length: 79 characters

Frequently occurring tokens include general web components such as "com," "https," and "www," as well as context-sensitive terms like "login" and "secure." Importantly, phishing-related tokens tend to have higher TF-IDF weights, indicating their strong contribution to classification decisions. This demonstrates that TF-IDF features provide high discriminative power, especially when combined with structural indicators.

3.4 Dataset Splitting and Model Training

The model was evaluated using Stratified K-Fold Cross Validation (k = 5) to maintain class balance across folds. Each fold contains 164,402 instances, with 657,608 used for training and 164,402 for testing per iteration.

This approach ensures:

- Each sample is tested exactly once
- Reduced sampling bias
- More reliable performance estimation

The Random Forest classifier was trained using combined structural and TF-IDF features. Performance metrics were computed for each fold and averaged to produce the final evaluation results, ensuring robustness and reproducibility.

3.5 Model Evaluation

The confusion matrix (Fig. 4) summarizes the classification results. The model correctly classified:

- 67,734 phishing URLs (True Positives)
- 82,489 legitimate URLs (True Negatives)

Misclassifications include:

- 2,917 False Positives
- 11,262 False Negatives

From these results:

- Phishing Precision: 0.96
- Phishing Recall: 0.86
- Phishing F1-score: 0.91
- Legitimate Precision: 0.88
- Legitimate Recall: 0.97
- Legitimate F1-score: 0.92

These results indicate that the model achieves high precision, meaning false alarms are minimal. However, the recall value suggests that some phishing URLs remain undetected.

From a cybersecurity perspective, false negatives are more critical than false positives, as undetected phishing attacks can lead to severe consequences. Therefore, improving recall without significantly degrading precision remains a key optimization objective.

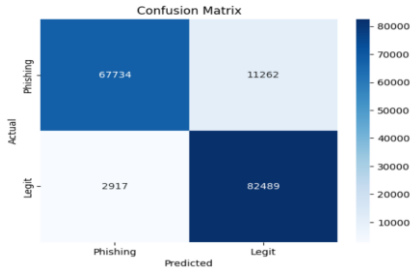

Fig 4: Confusion Matrix of URL Classification Results

Based on these results, the model achieved a precision of 0.96 for the phishing class, indicating that 96% of URLs predicted as phishing were indeed malicious. The recall for the phishing class reached 0.86, meaning that 86% of all actual phishing URLs were successfully detected. The corresponding F1-score was 0.91, demonstrating a strong balance between detection accuracy and completeness. For the legitimate class, the model obtained a precision of 0.88 and a recall of 0.97, resulting in an F1-score of 0.92. These findings indicate stable and consistent classification performance across both categories.

The high precision value in phishing detection suggests that the model effectively minimizes false alarms, which is crucial for maintaining usability in real-world applications. Nevertheless, the recall value indicates that a proportion of phishing URLs remains undetected. In practical cybersecurity environments, such false negatives may pose security risks, highlighting the need for further optimization to improve detection sensitivity while preserving high precision.

3.6 Error Analysis and Practical Scenario

Error analysis reveals two primary misclassification patterns:

1. False Negatives (Phishing classified as legitimate)
   Occur when phishing URLs closely mimic legitimate structures, including:
   - Use of HTTPS
   - Clean domain formatting
   - Minimal suspicious tokens
2. False Positives (Legitimate classified as phishing)
   Occur when legitimate URLs contain:
   - Security-related keywords ("login", "secure")

- High TF-IDF weights for suspicious tokens

These findings highlight a fundamental trade-off between sensitivity (recall) and specificity (precision). The model tends to prioritize precision, which is beneficial for usability but may reduce detection coverage.

3.7 Feature Importance Analysis

Feature importance analysis using mean decrease in impurity shows that:

- TF-IDF features dominate, confirming the importance of lexical patterns.
- Among structural features:
  - URL length and subdomain count are highly influential
  - Special characters and digit count have moderate importance
  - HTTPS has relatively low importance

This indicates a shift in phishing strategies, where attackers increasingly adopt HTTPS, making it a weak standalone indicator.

3.8 Comparative Discussion with Previous Studies

Compared to recent studies, the proposed approach demonstrates several advantages:

1. **Dataset Scale**. Most prior works use datasets below 20,000 URLs, while this study uses 822,010 URLs, significantly improving generalizability.
2. **Feature Engineering**. Previous studies rely mainly on structural features, whereas this work combines structural + TF-IDF (contextual text features).
3. **Evaluation Method**. The use of Stratified K-Fold Cross Validation provides more reliable results compared to single split validation.

Although some studies report higher accuracy, those results are often obtained from smaller datasets and less rigorous evaluation settings. The achieved F1-score of 0.91 demonstrates a strong balance between precision and recall in a large-scale.

Table 2. Comparative Analysis of Recent Phishing URL Detection Studies

Study	Year	Dataset Size	Feature Type	Reported Performance
Ramesh et al. [	2023	~10,000 URLs	Structural features	Accuracy 97.14%
Aprelia Windarni et al. [ ]	2023	~20,000 URLs	Pearson-selected features	Accuracy 96.3%
Mahmud and Wirawan [ ]	2024	~15,000 URLs	URL-based features	Accuracy 83.4%
Suwarno and Hardjianto [ ]	2024	~12,000 URLs	30 structural features	High accuracy reported
Proposed Study	2026	822,010 URLs	Structural + TF-IDF (1–3 grams)	F1-score 0.91 (phishing), 0.92 (legitimate)

Several key observations emerge from the comparison. First, most prior studies utilize relatively small datasets, typically ranging from 5,000 to 20,000 URLs. In contrast, the proposed study evaluates the model on a substantially larger dataset of 822,010 URLs, enhancing statistical robustness and generalizability. Second, earlier works predominantly rely on handcrafted structural features. While such approaches achieve high performance under controlled conditions, they may be less adaptable to evolving phishing patterns. The proposed study extends this paradigm by integrating structural attributes with TF-IDF-based lexical representations (unigram to trigram), enabling the model to capture contextual textual signals embedded within URLs.

Although some previous studies report slightly higher accuracy values, their evaluations are often based on smaller datasets or single train–test splits. By employing Stratified K-Fold Cross Validation, the proposed approach provides a more reliable performance estimation. The achieved F1-score of 0.91 for phishing detection demonstrates a strong balance between precision and recall in a large-scale setting.

4. CONCLUSION

This study demonstrates that a LoRA-enhanced CodeBERT model can effectively detect SQL Injection and Cross-Site Scripting (XSS) vulnerabilities in PHP source code while maintaining high parameter efficiency. By fine-tuning only approximately 0.7% of the model parameters, the proposed approach achieves an accuracy of 97% and a recall of 0.99 for vulnerable code, indicating strong performance in security-critical scenarios where undetected vulnerabilities can lead to significant risks. The results further show that the model is capable of capturing meaningful vulnerability patterns beyond simple surface-level indicators, reflecting its ability to learn context-aware and data-flow-related characteristics. In addition, the use of Low-Rank Adaptation (LoRA) reduces computational complexity, making the approach suitable for practical deployment in automated code analysis systems.

Future work should focus on extending the proposed model to support multiple programming languages and a wider range of vulnerability types beyond SQL Injection and XSS. Incorporating advanced code representations, such as Abstract Syntax Trees (AST) or Control Flow Graphs (CFG), may further improve the model's understanding of program structure and enhance detection performance. Moreover, integrating the model into real-time development environments, such as IDE plugins or continuous integration pipelines, could enable proactive vulnerability detection. Exploring hybrid approaches that combine deep learning with rule-based analysis is also recommended to further reduce false positives while maintaining high recall.

5. ACKNOWLEDGMENTS

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