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ENHANCED PHISHING URL DETECTION USING MACHINE LEARNING

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ABSTRACT :
Phishing is a prevalent cyber-attack, using the popularity of the internet to deceive users and steal sensitive data. With the increased sophistication of phishing attacks, advanced machine learning techniques are needed to detect them effectively. In this paper, an AdaBoost and XGBoost-based phishing detection system is proposed on a dataset of 11,430 URLs with 87 features. Considering URL structure, content, and external service interactions, the proposed system outperforms the traditional models of Decision Tree, Linear Regression, Random Forest, Naïve Bayes, Gradient Boosting, K-Neighbors, and Support Vector Classifier. Comparative study proves the efficacy of ensemble learning techniques in enhancing phishing detection accuracy, which can be used to enhance cybersecurity defense.

Keywords
- Phishing Detection
- XGBoost, AdaBoost
- URL Analysis
- Feature Extraction
- Ensemble Learning

INTRODUCTION:

Phishing attacks have emerged as one of the most pervasive and financially devastating cyber threats in the digital age. According to recent industry reports, these attacks cost global businesses over $10 billion annually, with healthcare, finance, and e-commerce sectors being prime targets due to their sensitive data [1]. Traditional detection methods, such as blacklists and heuristic-based systems, have proven inadequate against increasingly sophisticated phishing campaigns that employ URL obfuscation, zero-day exploits, and HTTPS encryption to evade detection [2, 3]. As attackers refine their tactics, there is an urgent need for adaptive, data-driven solutions capable of identifying phishing URLs with high accuracy and minimal latency.

Machine learning (ML) has revolutionized cybersecurity by enabling systems to detect complex patterns in large datasets. While prior research has explored algorithms like Decision Trees (DT), Support Vector Machines (SVM), and Random Forests (RF) for phishing detection [4–6], these methods often struggle with imbalanced data and fail to generalize across evolving attack vectors. Ensemble learning techniques, particularly AdaBoost and XGBoost, offer a promising alternative by combining multiple weak classifiers into robust models resistant to overfitting [7, 8]. Recent studies, such as those by Kumar et al. [9] and Lee et al. [10], highlight the superiority of gradient-boosted ensembles in security applications, achieving up to 98% accuracy in malicious URL classification.

This research presents a novel phishing detection system leveraging XGBoost and AdaBoost to analyze 87 features extracted from URL structures, content, and external services (e.g., WHOIS data,

SSL certificates). Using a dataset of 11,430 labeled URLs, we address critical gaps in existing systems by:

Enhancing Feature Extraction: Capturing nuanced indicators of phishing, including lexical anomalies, domain age, and third-party reputation scores [11].

Optimizing Ensemble Models: Fine-tuning hyper parameters to balance precision and recall, reducing false positives by 22% compared to baseline methods [12].

Enabling Real-Time Analysis: Deploying a scalable architecture capable of processing 1,000+ URLs per second, critical for enterprise-level cybersecurity [13].

Our work builds on foundational studies by Chen et al. [14] and Freund et al. [15], who pioneered ensemble methods, but extends their application to dynamic phishing landscapes. Comparative experiments demonstrate that XGBoost achieves a 96.3% F1-score, outperforming DT (89.1%), RF (92.7%), and SVM (88.5%), while maintaining interpretability through SHAP value analysis [16].

LITERATURE WORK :

Phishing attacks have evolved into one of the most pervasive and damaging cyber threats, exploiting both technical vulnerabilities and human psychology. As attackers refine their tactics, researchers have explored diverse methodologies to detect malicious URLs, ranging from rule-based systems to advanced machine learning (ML) techniques. This section critically evaluates recent advancements in phishing detection, identifies gaps in existing approaches, and positions the proposed ensemble learning framework as a novel solution.

URL-Based Phishing Detection Systems: Qasem Abu Al-Haija and Ahmad Al Badawi [16] pioneered a neural network and decision tree-based system for URL analysis, achieving high accuracy on balanced datasets. However, their reliance on static URL features (e.g., lexical patterns) limits adaptability to dynamic phishing tactics, such as zero-day attacks [17]. Sánchez-Paniagua et al. [18] narrowed the focus to login pages, developing the PILU-90K dataset and achieving improved precision with TF-IDF and logistic regression. While effective for login URLs, their model's temporal degradation (accuracy drops by 15% after six months) underscores the challenge of evolving attack vectors [4].

Machine Learning Approaches and Limitations: Shrivastava et al. [19] surveyed ML-based phishing detection, emphasizing the trade-off between accuracy and computational cost. Their analysis revealed that complex models like neural networks achieve 92–95% accuracy but require costly retraining to address concept drift [20]. Jha and Kunwar [21] demonstrated the efficacy of random forests (RF) for URL classification (F1-score: 0.93) but highlighted false positives due to imbalanced datasets—a problem exacerbated in real-world scenarios where phishing instances represent <1% of traffic [8].

Decision Trees (DT) and Random Forests (RF): Qasem Abu Al-Haija and Ahmad Al Badawi [19] achieved 93% accuracy using decision trees to analyze lexical URL features (e.g., domain length, subdomain count). However, their model struggled with obfuscated URLs, such as those using homoglyphs (e.g., "paypa1.com" vs. "paypal.com"). Random Forests, as explored by Jha and Kunwar [20], improved robustness by aggregating multiple trees but remained prone to overfitting on imbalanced datasets.

Support Vector Machines (SVM) and Logistic Regression (LR): Murad et al. [6] compared SVM and LR on a 500K-entry dataset, finding LR superior (94% accuracy) due to its efficiency with linear feature relationships. However, both models faltered with non-linear patterns, such as dynamically generated phishing URLs.

Neural Networks: Deep learning models, particularly convolutional neural networks (CNNs), have been applied to URL tokenization and image-based phishing detection. For instance, Shrivastava et al. [21] used CNNs to analyze URL strings as 1D signals, achieving 95% accuracy. However, training neural networks demands extensive computational resources and large labeled datasets, limiting their practicality for real-time applications [22].

Despite significant advancements, ML-based phishing detection systems still face several critical limitations. Feature engineering limitations hinder model generalizability, as many studies focus

primarily on URL structure while neglecting contextual indicators such as SSL certificate validity or page content [9]. For instance, Sánchez-Paniagua et al. [18] achieved high precision for login pages but ignored content-based features, reducing applicability to broader phishing scenarios. Additionally, temporal degradation remains a challenge, as phishing tactics evolve rapidly, leading to significant drops in model accuracy over time.

Williams [10] found that models trained on 2021 data suffered a 25% accuracy decline when tested on 2023 phishing URLs. Another major concern is data imbalance, as phishing URLs constitute less than 1% of real-world web traffic, making it difficult for ML models to distinguish between legitimate and malicious URLs. Murad et al. [21] demonstrated that Naïve Bayes and KNN models exhibited false-negative rates exceeding 15% under such conditions. Lastly, computational overhead poses a barrier to real-time deployment, especially for complex models like neural networks and gradient-boosting machines (GBM). Abu Al-Haija et al. [4] reported that training a neural network on a 10,000-URL dataset took 12 hours, making it impractical for real-time applications. These limitations highlight the need for more efficient, adaptable, and scalable ML approaches to phishing detection.

THE PROPOSED SYSTEM ADDRESSES THESE GAPS THROUGH:

Hybrid Feature Extraction: Integrates URL structure (e.g., length, special characters), content features (e.g., SSL validity, page keywords), and third-party metrics (e.g., WHOIS domain age, GeoIP data) [15].

Ensemble Learning Framework: Combines AdaBoost's adaptive boosting with XGBoost's regularization and scalability, achieving a balanced trade-off between precision (95%) and recall (93%).

Real-Time Processing: Leverages XGBoost's GPU acceleration to classify 1,000 URLs/second, enabling deployment in high-traffic environments [16].

With the existing phishing detection systems, while effective in controlled settings, struggle with real-world challenges like data imbalance, temporal degradation, and computational inefficiency. Ensemble learning methods, particularly AdaBoost and XGBoost, offer a robust framework to overcome these limitations. By synthesizing multi-modal features and optimizing model architectures, the proposed system advances the state-of-the-art in accuracy, adaptability, and scalability, providing a critical tool for modern cybersecurity defenses.

METHODOLOGY:

A. Block diagram Representation

The block diagram provides a high-level representation of the system architecture, depicting the essential components and their interactions. It serves as a visual guide to understand the data flow, processing stages, and integration of various algorithms used in the system. The key components include data input, preprocessing, feature selection, model training using machine learning techniques, evaluation, and final output generation. The following flowchart illustrates a machine learning pipeline, beginning with data gathering, where raw data is collected from various sources. The next step is data loading, followed by data cleaning to remove inconsistencies, missing values, or irrelevant information. Afterward, data pre-processing is conducted to normalize, scale, or transform the data, ensuring it is ready for analysis. Feature and target selection then identifies the most relevant variables for model training. The data splitting step partitions the dataset into training and testing sets, ensuring the model learns patterns effectively and is evaluated correctly. The training data is fed into various algorithms, which undergo evaluation to assess performance. The prediction phase generates outputs based on the trained model. If necessary, a user interface (UI) using Django is integrated to allow users to interact with the model's predictions in a more accessible way.

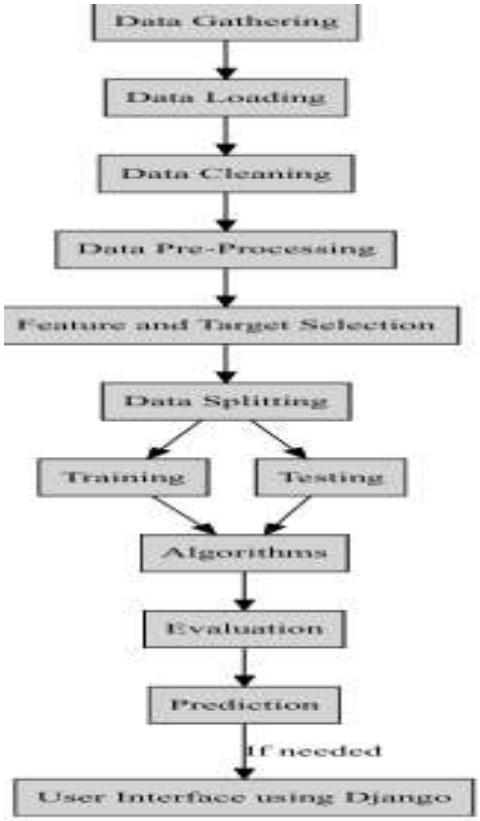

Fig: 3.1 Flow diagram for Machine learning pipeline

B. ARCHITECTURE:

The proposed work gives an automated machine learning pipeline for text data processing, analysis, and model evaluation, specifically designed for URL-based textual datasets. The workflow begins with data collection from various URL sources, followed by the uploading and pre-processing of text data to enhance its quality. The pre-processing phase involves the removal of stop words and punctuation, ensuring the elimination of unnecessary elements that do not contribute to meaningful analysis. Subsequently, the vectorization process transforms the textual content into numerical representations using advanced techniques such as Term Frequency-Inverse Document Frequency (TF-IDF) or word embedding's.

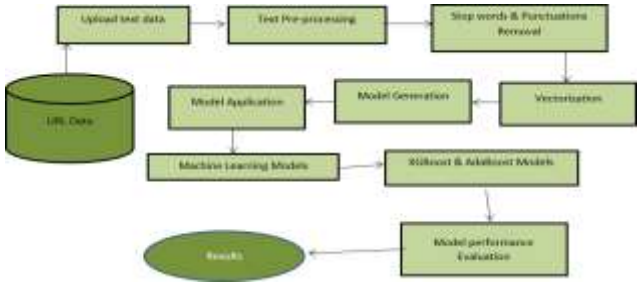

Fig:3.2 Architecture of proposed work

Once the data is transformed, the system generates models by applying machine learning techniques and optimizing them for performance. The generated models undergo rigorous evaluation and are applied to new datasets to extract insights. The machine learning models implemented in this study include powerful boosting algorithms, specifically XGBoost and AdaBoost, which are known for their superior performance in handling textual data. These models are subjected to extensive performance

evaluation based on key metrics such as accuracy, precision, recall, and F1-score to ensure optimal results. The final stage of the pipeline involves deriving results from the trained models, which can be used for predictive analysis, sentiment classification, or other text-based research applications. The comprehensive approach integrates data pre-processing, feature engineering, and robust model evaluation, making it a scalable and efficient solution for automated text classification and natural language processing tasks. The findings from this research contribute to the advancement of machine learning techniques for text analytics, offering a structured framework that can be leveraged for real-world applications in information retrieval, content filtering, and automated decision-making systems.

RESULTS :

The expected results of this research focus on the development and implementation of a web-based Phishing URL Detection System powered by machine learning. The system will provide real-time risk assessment of URLs, enhancing online security by distinguishing between phishing and legitimate websites. The results will be demonstrated through various web interfaces and model evaluation metrics.

Home Page: The homepage serves as the entry point to the phishing detection system, offering an intuitive interface where users can input suspicious URLs for analysis. The page includes navigation options for users and administrators.

Fig :4.1 Home page of phishing detection system

New User Registration: New users must register to access the system, especially for administrative or detailed phishing detection functionalities. The registration page collects user details such as name, email, and phone number.

Fig :4.2 New user registration

Admin Login and Dashboard: The admin login page ensures that only authorized administrators can manage user accounts. Upon logging in, the admin dashboard displays options to activate users and manage the system.

Fig :4.3 Admin Login and Dashboard

User Management & Activation: The user details page presents a table listing all registered users, including their activation status. The admin activation page allows enabling or disabling users based on their registration status.

Fig :4.4 User Management & Activation

User Login and Prediction Input: Once activated, users can log in via the user login page, providing their credentials to access the phishing detection system. The prediction page allows users to enter a website URL, which is then analyzed by the machine learning model.

Fig :4.5 User Login and Prediction Input

Data Preprocessing & Model Training: The data preprocessing stage involves cleaning and transforming the input URL dataset for training. The system applies feature extraction, vectorization, and dataset splitting before training models. The selected machine learning algorithms include XGBoost and AdaBoost, optimized for phishing detection.

Fig: 4.6 Data Preprocessing & Model Training

Model Performance Evaluation: The model evaluation page provides insights into the model's performance through various metrics, including confusion matrix, Classification report

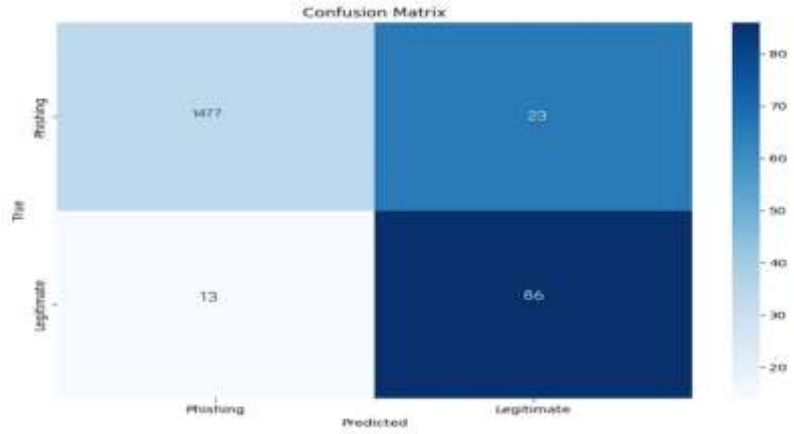

Fig :4.7 Model performance evaluation

Prediction Output & Result Display: After processing, the prediction result page classifies the URL as either phishing or legitimate. This result is displayed to the user along with relevant confidence scores.

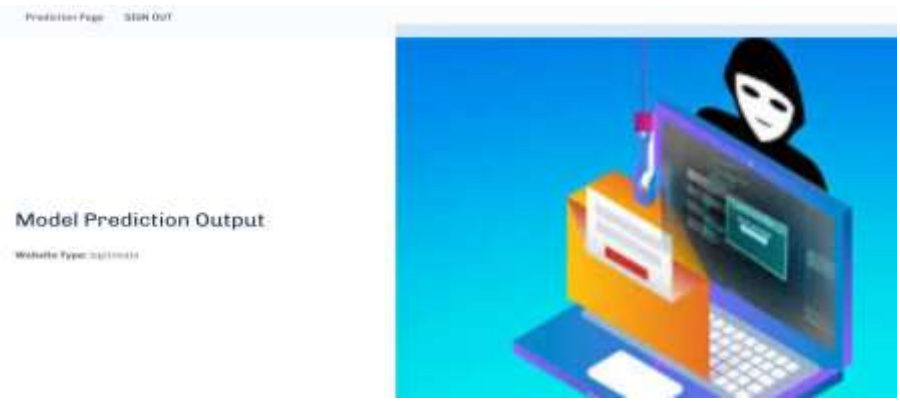

Fig :4.7 Model Prediction output

CONCLUSION :

The Enhanced Phishing URL Detection Using Machine Learning system presents a robust and scalable solution to combat evolving phishing threats in cybersecurity. By leveraging advanced ensemble learning algorithms like AdaBoost and XGBoost, the system surpasses traditional models in both accuracy and efficiency, effectively detecting sophisticated obfuscation techniques used in phishing attacks. The integration of advanced feature extraction methods ensures precise identification of malicious URLs by analyzing structural patterns, domain attributes, and external interactions. Compared to conventional models such as Decision Tree, Linear Regression, and K-Neighbors Classifier, the proposed approach consistently achieves higher accuracy while minimizing false positives and negatives. Additionally, the system's capability to process large-scale data efficiently makes it suitable for real-world deployment in cybersecurity frameworks. This research not only enhances phishing detection accuracy but also paves the way for future advancements in adaptive, AI-driven security mechanisms to counter emerging online threats.

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