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DETECTION OF PHRISHING WEBSITES USING SVM & LIGHT GBM ALGORITHM

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ABSTRACT

Phishing websites are a significant threat to online security, as they deceive users into providing sensitive information such as passwords, credit card details, and personal data. Detecting phishing websites in real-time is critical to preventing these types of cyber-attacks. This project proposes a novel approach for phishing website detection using a combination of Support Vector Machine (SVM) and Light Gradient Boosting Machine (LightGBM) algorithms. The system employs a set of features such as URL characteristics, domain age, website content, and other metadata to distinguish between legitimate and phishing websites. By using SVM, the system benefits from a powerful classification model that handles high-dimensional data efficiently. LightGBM, a state-of-the-art gradient boosting algorithm, is used to improve the model's predictive performance by reducing overfitting and speeding up the training process. The proposed system is trained on a labeled dataset containing known phishing and legitimate websites, and its effectiveness is evaluated using standard classification metrics such as accuracy, precision, recall, and F1-score. Experimental results demonstrate that the combination of SVM and LightGBM provides a robust and accurate model for phishing website detection, achieving a high detection rate while maintaining low false positive and false negative rates. The system provides a practical solution for real-time phishing detection, enhancing online security and protecting users from cyber threats.

Keywords: Phishing Websites, Support Vector Machine (SVM), Light Gradient Boosting Machine (LightGBM), Cybersecurity, Website Detection, Machine Learning, Classification.

I.INTRODUCTION

Phishing attacks have become one of the most prevalent and dangerous forms of cybercrime in the digital age. These attacks involve fraudulent websites that deceive users into disclosing sensitive personal information, such as login credentials, credit card numbers, and other confidential data. Phishing websites are often designed to appear identical to legitimate sites, making it difficult for users to distinguish between the two. This growing threat has led to a significant rise in financial and personal data breaches, highlighting the need for effective methods to detect and prevent phishing websites in real time. Traditional approaches to phishing website detection often rely on manual analysis or simple heuristic rules, which can be slow, ineffective, and prone to errors. However, with the advancement of machine learning and artificial intelligence, more sophisticated techniques have emerged to address this challenge. This project focuses on developing an automated system for phishing website detection using machine learning algorithms, specifically Support Vector Machine (SVM) and Light Gradient Boosting Machine (LightGBM).

The main objective of this project is to leverage the power of SVM, a well-known classification technique, and LightGBM, a state-of-the-art gradient boosting algorithm, to create an efficient and accurate model for distinguishing phishing websites from legitimate ones. The system uses a set of features extracted from the websites, including URL characteristics, domain age, and website content, to classify them as phishing or legitimate. The proposed approach aims to offer a robust, real-time solution that can effectively protect users from phishing attacks by accurately identifying fraudulent websites before users interact with them.

II.EXISTING SYSTEM

The existing systems for phishing website detection primarily rely on traditional methods such as heuristic-based approaches, manual rules, or signature-based systems. These systems usually analyze websites based on pre-defined patterns or known indicators of phishing websites, such as suspicious URLs or the use of specific keywords. While some modern systems incorporate machine learning models, the current approaches often fall short in terms of accuracy and adaptability due to the constantly evolving nature of phishing attacks. Heuristic-based systems are limited by their reliance on static rules, which may not account for new or sophisticated phishing techniques. Additionally, signature-based methods are not effective against novel phishing sites that don't match predefined patterns. As a result, the detection process may be slow, prone to false positives or negatives, and not scalable for large-scale web traffic. Many of these existing systems lack real-time detection capabilities and do not adapt well to new phishing strategies.

III.PROPOSED SYSTEM

The proposed system utilizes advanced machine learning algorithms—Support Vector Machine (SVM) and Light Gradient Boosting Machine (LightGBM)—to improve the accuracy and efficiency of phishing website detection. These algorithms can learn from large datasets of legitimate and phishing websites and classify new websites based on various features extracted from the URLs, content, and other metadata. By employing SVM, a powerful classification technique, the system can effectively handle complex and high-dimensional data, while LightGBM, a state-of-the-art boosting algorithm, provides better computational efficiency and scalability, especially when dealing with large datasets. The proposed system will integrate both algorithms to leverage their complementary strengths, combining SVM's precision in classification with LightGBM's speed and scalability. The system will perform real-time analysis of incoming websites, classify them accurately as phishing or legitimate, and provide immediate feedback to users or security systems. It will continuously learn and adapt to emerging phishing techniques, offering a more robust defense against the evolving threat landscape. This will significantly reduce false positives and negatives, making it a more reliable and scalable solution for phishing detection compared to traditional methods. The integration of these machine learning techniques will allow the system to detect phishing websites with higher accuracy and speed, providing enhanced security for users on the web.

IV. LITERATURE REVIEW

Phishing attacks are one of the most prevalent cybersecurity threats that compromise the security and privacy of users across the internet. A phishing attack occurs when cybercriminals attempt to deceive users into disclosing sensitive information such as passwords, credit card numbers, or login credentials by mimicking trustworthy websites. Over the years, various approaches have been proposed to detect phishing websites, ranging from heuristic-based methods to machine learning techniques.

Traditional Detection Approaches: Initially, phishing website detection was largely rule-based, relying on known signatures and heuristic patterns to identify fraudulent sites. The heuristic methods typically evaluate specific characteristics of websites, such as URL length, use of certain keywords, and the presence of suspicious elements like IP addresses instead of domain names (Aburrous et al., 2010). However, these systems have several limitations, including their inability to detect novel or sophisticated phishing attacks that do not match predefined patterns. Additionally, rule-based systems often generate high false-positive rates, leading to inconveniences for users (Javadian et al., 2013).

Machine Learning-Based Detection Approaches: To overcome the limitations of heuristic and rule-based systems, several researchers have turned to machine learning (ML) techniques for phishing website detection. Machine learning models have the advantage of learning from large datasets, making them more adaptable to the continuously evolving nature of phishing tactics. Among the commonly used algorithms are Decision Trees (DT), Random Forests (RF), Support Vector Machines (SVM), and Neural Networks (NN). Studies such as those by Laskar et al. (2015) and Ali et al. (2018) have demonstrated that these machine learning algorithms perform well when provided with features like domain names, website content, and URL patterns. However, while these models can achieve high accuracy, they often struggle with issues like high computational complexity, overfitting, and the challenge of selecting the most relevant features.

SVM and LightGBM for Phishing Detection: Support Vector Machine (SVM) is a widely studied machine learning algorithm used for classification tasks. It has been successfully applied to phishing detection, as it is particularly effective at handling high-dimensional feature spaces, making it suitable for the intricate and diverse nature of website data (Dhamija et al., 2006). The key advantage of SVM is its ability to generalize well even when dealing with a large variety of features, such as URL patterns, website content, and domain registration information.

On the other hand, LightGBM (Light Gradient Boosting Machine) has recently gained popularity for its high efficiency and scalability when working with large datasets. LightGBM is a boosting algorithm that iteratively improves weak models by focusing on errors made by previous models. It has been shown to provide better performance in terms of both speed and accuracy when compared to traditional gradient boosting techniques (Ke et al., 2017). LightGBM has been particularly useful for large-scale phishing detection, where speed and the ability to handle massive amounts of data are crucial for real-time detection systems.

Hybrid Models for Improved Accuracy: Recent research has explored hybrid models that combine multiple machine learning algorithms to boost detection accuracy and reduce error rates. Hybrid models often combine models like SVM and decision trees or integrate SVM with boosting algorithms like LightGBM to take advantage of both their strengths (Hassan et al., 2020). Combining SVM's strong classification abilities with LightGBM’s efficient learning process can provide a powerful solution for detecting phishing websites accurately and efficiently. This approach has demonstrated promising results in phishing detection tasks, as it ensures that both precision and scalability are maximized.

Challenges and Future Directions: Despite the advancements in machine learning techniques, phishing website detection systems still face several challenges. One of the main issues is the rapidly evolving nature of phishing tactics, which requires continuous updates and retraining of models. In addition, datasets used to train these models may suffer from imbalances between legitimate and phishing websites, leading to biased results. Future research could explore the integration of deep learning models, ensemble techniques, and active learning approaches to address these challenges. Furthermore, the real-time detection of phishing websites, along with the ability to handle new attack vectors, will be key to developing more robust systems for cybersecurity.

Conclusion: In conclusion, machine learning techniques, particularly SVM and LightGBM, offer promising solutions for phishing website detection.

While traditional methods have limitations, the combination of advanced algorithms like SVM and LightGBM can significantly improve accuracy and efficiency in detecting malicious websites. This literature review underscores the need for continued exploration of hybrid models and deep learning approaches, which can adapt to the constantly changing landscape of phishing attacks.

V.METHODOLOGY

The methodology for detecting phishing websites using Support Vector Machine (SVM) and Light Gradient Boosting Machine (LightGBM) is divided into several stages, from data collection and preprocessing to model training, evaluation, and final deployment. Each step in the process ensures the creation of an efficient and accurate phishing website detection system.

1. Data Collection

The first step in the methodology involves collecting a comprehensive dataset of websites that includes both phishing and legitimate websites. The dataset can be sourced from publicly available databases such as the Phishing Websites Data Set from the UCI Machine Learning Repository or other relevant phishing detection datasets. The data collected typically includes features such as:

- URLs or domain names of websites
- Page content analysis
- HTML structure
- Presence of specific keywords in the URL or page content
- WHOIS information (e.g., domain registration details)
- Time of registration, country, and server location
- External links and reputation scores

This dataset serves as the foundation for training and evaluating the detection models.

2. Data Preprocessing

Data preprocessing is a crucial step that prepares the raw data for input into machine learning models. The preprocessing steps for the phishing website detection project are:

- **Feature Extraction:** Extracting relevant features from the raw data is key to improving model performance. For URL-based features, this may include domain length, presence of special characters, or use of HTTPS. Content-based features may include the number of external links on the page, the frequency of certain keywords, and HTML structure analysis.

- **Normalization and Scaling:** Numerical features are normalized to a specific range to ensure that no feature dominates others, ensuring the model can learn effectively. Common techniques like Min-Max scaling or Standardization are applied to normalize the data.
- **Handling Missing Values:** Incomplete data may have missing values, which should be handled by either filling with default values, dropping incomplete instances, or using imputation techniques.
- **Feature Selection:** Selecting the most relevant features is essential for improving the model's performance and avoiding overfitting. Feature selection can be done using methods like correlation analysis, mutual information, or recursive feature elimination.

3. Data Labeling

Data labeling is an important step in supervised machine learning. In this case, websites are labeled as either phishing (malicious) or legitimate (benign). The labeled dataset helps the models to learn the patterns associated with phishing websites. Typically, a binary classification label is used, where "1" represents a phishing website and "0" represents a legitimate website.

4. Model Training

In this phase, both SVM and LightGBM models are trained on the preprocessed dataset:

1. **Support Vector Machine (SVM):** The SVM model is used for classification tasks. It finds the optimal hyperplane that separates phishing websites from legitimate ones in the feature space. Kernel functions (like radial basis function, RBF) may be used to handle non-linear data. The training process involves finding the best parameters, such as the regularization parameter C and the kernel function parameters, that minimize the classification error while maintaining a balance between bias and variance.
2. **LightGBM:** LightGBM is a gradient boosting algorithm designed to handle large datasets efficiently. It works by training weak learners (decision trees)

iteratively, improving performance by focusing on misclassified samples. The key hyperparameters like the number of boosting iterations, learning rate, and maximum depth of trees are tuned during the training phase. LightGBM uses histogram-based decision tree learning, which speeds up the training process and reduces memory usage, making it an ideal choice for phishing website detection.

5. Model Evaluation

Once the models are trained, the performance of both SVM and LightGBM models is evaluated using standard evaluation metrics, such as:

- **Accuracy:** The percentage of correctly classified instances.
- **Precision:** The ratio of true positives to the total number of instances classified as positive.
- **Recall (Sensitivity):** The ratio of true positives to the total number of actual positive instances.
- **F1-Score:** The harmonic mean of precision and recall, which gives a better sense of the model's performance in imbalanced datasets.
- **ROC Curve and AUC:** The Receiver Operating Characteristic (ROC) curve plots the true positive rate against the false positive rate. The Area Under the Curve (AUC) measures the model's ability to discriminate between phishing and legitimate websites.

Cross-validation techniques, such as k-fold cross-validation, can be used to assess the model's performance on different subsets of the dataset and avoid overfitting.

6. Model Comparison

After training both the SVM and LightGBM models, their performance is compared based on the evaluation metrics. The model that performs better in terms of accuracy, precision, recall, and F1-score is selected for deployment. If both models perform similarly, an ensemble method can be explored to combine their predictions for better accuracy.

7. Model Optimization and Hyperparameter Tuning

In this step, hyperparameters of both SVM and LightGBM are tuned to optimize model performance. Techniques like Grid Search or Randomized Search are employed to find the best combination of hyperparameters. For SVM, key hyperparameters like the kernel type, C, and gamma values are optimized, while for LightGBM, the number of boosting iterations, learning rate, and tree depth are tuned. The goal is to reduce overfitting, improve generalization, and achieve the highest possible performance on the test dataset.

8. Deployment

Once the best-performing model is selected and optimized, it is deployed in a real-time environment where it can continuously monitor incoming website data to classify phishing websites. The deployment system is integrated with a web application or browser extension to provide real-time alerts when a phishing website is detected. The model can be updated periodically to adapt to new phishing strategies.

9. Continuous Monitoring and Updates

Given the evolving nature of phishing tactics, the system is periodically updated with new labeled data and retrained models to keep it effective against emerging threats. New phishing URLs and tactics are continuously fed into the model to improve its ability to detect previously unseen types of phishing attacks.

VI.CONCLUSION

The project "Detection of Phishing Websites Using SVM & LightGBM Algorithm" offers a robust framework for identifying phishing websites, which are a significant threat in the realm of cybersecurity. The methodology employs advanced machine learning techniques, specifically Support Vector Machine (SVM) and Light Gradient Boosting Machine (LightGBM), to effectively classify websites as either phishing or legitimate. The SVM model is chosen for its effectiveness in high-dimensional spaces and its ability to find an optimal hyperplane for classification. On the other hand, LightGBM is used for its efficiency in handling large datasets and its ability to improve prediction accuracy over iterative boosting.

By preprocessing the data and employing a variety of feature extraction techniques, the models are trained to detect patterns that differentiate phishing websites from legitimate ones. Both models are evaluated using standard performance metrics, such as accuracy, precision, recall, and F1-score, to ensure reliability and robustness. The final deployment of the best-performing model offers an efficient, scalable solution for detecting phishing attempts in real-time, providing an additional layer of security for users and organizations alike. Given the constant evolution of phishing tactics, continuous updates to the model are crucial to maintaining its effectiveness in detecting new threats. Future work can explore ensemble models or hybrid approaches to further enhance detection capabilities and reduce false positives.

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