# PHISHING DETECTION SYSTEM THROUGH MACHINE LEARNING BY URL

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**Abstract:** Phishing attacks are among the most severe cybersecurity threats in the digital world. With the exponential increase in cybercrimes, traditional security measures struggle to detect and prevent phishing activities efficiently. This study explores a phishing detection system utilizing hybrid machine learning techniques to classify and avoid phishing URLs. The research proposes a model combining Decision Tree (DT), Logistic Regression (LR), and Support Vector Classifier (SVC) to form an ensemble method named LSD. The dataset used consists of 11,000+ URLs with various phishing and legitimate attributes. The study evaluates performance using accuracy, precision, recall, F1-score, and specificity metrics. The findings indicate that the LSD model outperforms individual classifiers, achieving high accuracy and improved detection rates. Future research should focus on real-time phishing detection and the integration of advanced deep learning methodologies for enhanced cybersecurity.

**Keywords:** Phishing Detection, Cybersecurity, URL Classification, Hybrid Model, Data Security.

## I. INTRODUCTION

The internet plays a crucial role in many aspects of human life. It is a global network that connects computers through phonelines, fiber optic cables, wireless, and satellite communication. This network allows access to information stored on hosts and servers around the world. Communication across the internet takes place using the TCP/IP protocol [4]. The internet is not owned by any government but is managed collectively by universities, organizations, and research agencies [1].

The internet has transformed almost every field of life including entertainment, education, medicine, industry, freelancing, and research. It provides great opportunities for searching data and conducting studies [5]. Email is one of the fastest means of communication, allowing the exchange of files, videos, and images globally [10]. Similarly, e-commerce has enabled people to conduct business and financial transactions across the world. Online shopping, led by platforms like Amazon, has become one of the largest uses of the internet. Social media applications such as Facebook, Instagram, and WhatsApp have also made communication faster and more accessible [8].

During the COVID-19 pandemic, the internet became an essential tool for online classes, business meetings, and the sharing of information [7]. However, the rapid increase in data sharing also brought risks such as cyberattacks and data theft.

To ensure safe usage, maintaining privacy policies has become a necessity [9]. Despite the many benefits, the growing dependence on the internet has also led to serious challenges, particularly in the form of cybercrimes [2].

One of the most common threats is phishing. Phishing is a cyberattack where users are tricked into entering sensitive information, such as usernames, passwords, or credit card numbers, into fake websites that closely resemble legitimate ones [3]. These attacks target individuals, companies, and financial institutions, leading to significant losses of money, privacy, and data [11]. The FBI reported that phishing scams resulted in losses of at least $2.5 billion between 2013 and 2016.

To tackle this issue, there is a need for intelligent systems that can identify phishing websites quickly and accurately. This project uses machine learning algorithms to detect phishing URLs by analyzing different features such as URL length, the use of special characters, the presence of HTTPS, and the number of dots in the address [6]. Models like Logistic Regression, Support Vector Classifier, and Decision Tree are applied to classify websites as phishing or legitimate [2].

In addition, a hybrid model combining all three algorithms is developed to improve detection accuracy [11]. The system works in real-time to alert users before they fall victim to phishing attacks [8]. Apart from providing technical protection, it also helps in raising awareness among users about online security threats [9]. Reported cases, such as PayPal login scams and attacks on large healthcare providers in Australia, highlight the growing need for such systems [2].

In conclusion, while the internet offers countless advantages in communication, commerce, education, and entertainment, it also poses risks like phishing. By applying machine learning techniques to phishing detection, this project aims to provide a smart, automated, and reliable solution that ensures safe browsing and protects users from online fraud [7].

## II. RELATED WORK

### Existing Research and Solutions:

The existing systems in cybersecurity and phishing detection are limited in their ability to provide real-time, intelligent responses to evolving threats. Traditional

approaches, such as Applied Behavior Analysis (ABA), have been effective in structured environments like education and behavior correction [1], but they do not translate well to the dynamic digital space. In smart platforms and IoT-based environments, data such as motion, behavioral, and physiological inputs could strengthen defenses, yet these remain underutilized in cybersecurity [6]. Most current phishing detection relies on static blacklists, rule-based models, or single machine learning methods like Support Vector Machines (SVM) and Random Forests [2]. These techniques are rigid, struggle with zero-day attacks, and cannot easily adapt to new phishing strategies [7].

Another limitation lies in the complexity of phishing data, which includes textual URL attributes, SSL certificate details, and domain statistics [3]. Processing such high-dimensional datasets in real-time remains a challenge. Cyberattacks are also becoming more advanced, with threats like ransomware, spear-phishing, and social engineering targeting critical sectors such as healthcare, finance, and energy [4]. Static systems lacking adaptive feedback loops are unable to keep pace, leaving infrastructures highly vulnerable [2]. Attacks on transportation or healthcare data could even cause physical harm and large-scale disruptions, proving that cybersecurity in smart environments requires adaptive and intelligent solutions [8].

The disadvantages of existing systems include their inability to handle complex datasets efficiently, dependence on large amounts of labeled data, and vulnerability to inaccuracies caused by incorrect labeling [11]. To overcome these shortcomings, the proposed system introduces a phishing detection framework powered by machine learning. It uses a hybrid approach that combines Logistic Regression (LR), Support Vector Classifier (SVC), and Decision Tree (DT), collectively forming the LSD model [7]. This ensemble leverages the strengths of individual classifiers to deliver higher accuracy and resilience against phishing threats [2].

The system is trained on a dataset of more than 11,000 URLs, including both phishing and legitimate sites [3]. With canopy feature selection, cross-validation, and grid search optimization, it ensures accurate and efficient prediction [11]. Additionally, user sentiment and interaction with phishing content are incorporated into the learning process, allowing the model to adapt over time [2]. The advantages of the proposed system include improved classification performance through hybrid modeling, real-time phishing URL detection, and intelligent adaptability to evolving cyber threats [7]. Ultimately, this system provides a robust and dynamic defense, making it far more effective than conventional approaches [11].

Harun et al. [1] discussed the significance of machine learning in strengthening cybersecurity systems, emphasizing its role in handling dynamic and complex threats. Their study provided an overview of how supervised and unsupervised techniques can be applied to anomaly detection, intrusion prevention, and phishing detection. While the paper highlighted the potential of machine learning in improving adaptability, it also noted challenges related to data imbalance and computational costs.

Akanchha [2] explored phishing detection using hybrid models that combine multiple classifiers. The study demonstrated that hybrid approaches outperform single-model techniques by leveraging the strengths of different algorithms. The research confirmed improved accuracy and robustness in detecting phishing attempts, particularly against zero-day attacks. However, it also pointed out the increased complexity in model training and integration.

Zouina and Outtaj [3] proposed a lightweight phishing detection system designed to minimize computational overhead while maintaining high detection accuracy. Their model focused on URL-based features and heuristic techniques, which made it suitable for resource-constrained environments. Although the lightweight design offered efficiency, the authors acknowledged its limitations in detecting more sophisticated phishing websites that employ obfuscation techniques.

Prakash et al. [4] introduced *PhishNet*, a predictive blacklisting approach aimed at extending traditional blacklist methods. By predicting variants of known phishing URLs, their system improved detection coverage and reduced reliance on static blacklists. While effective against large-scale phishing campaigns, the approach had limitations when handling previously unseen phishing domains.

Cao et al. [5] proposed automated detection techniques based on individual whitelists, shifting focus from blacklisting to trusted sources. Their method enhanced resistance to phishing by relying on legitimate, user-specific whitelists. This approach showed high accuracy in preventing phishing attacks but faced challenges in scalability and the initial setup of trusted lists.

## III. Research Methodology

This study adopts a multi-faceted approach to investigate Phishing Detection Through Machine Learning by URL. The methodology is divided into the following key phases[12].

### *A.* Data Collection:

Data was gathered from multiple sources, including government reports, cybersecurity incident logs, smart city frameworks, and academic literature. Additionally, structured surveys and expert interviews were conducted to gain insights from cybersecurity professionals, policymakers, and AI researchers. The dataset consists of phishing and legitimate URL attributes collected from various sources, including open-source cybersecurity databases.

### *B.* Feature Selection and Pre-processing:

A critical step in AI model development is identifying relevant features for phishing detection. The selected features include URL structure attributes, domain characteristics, HTTP security protocols, and website behaviour patterns. The collected data underwent pre-processing, including:

**Noise Reduction:** Eliminating redundant or irrelevant attributes to improve model efficiency.

**Normalization:** Standardizing feature values to ensure consistency across the dataset. Extracting relevant URL-

based indicators such as domain age, HTTPS usage, and suspicious keyword patterns.

### *C.* AI Model Development

Extracting relevant URL-based indicators such as domain age, HTTPS usage, and suspicious keyword patterns.

**Support Vector Machines (SVM):** Applied for binary classification of phishing and legitimate URLs[13][14]

**Random Forest:** Used for decision-making based on ensemble learning.

**Approximate Bayes (ABayes):** A probabilistic model used to classify phishing threats based on URL feature distributions.

**Deep Learning Models**: Combines Logistic Regression (LR), Support Vector Classifier (SVC), and Decision Tree (DT) to enhance classification accuracy and reduce false positives[15].


**Fig 1:AI Models used for Phishing**

## System Architecture

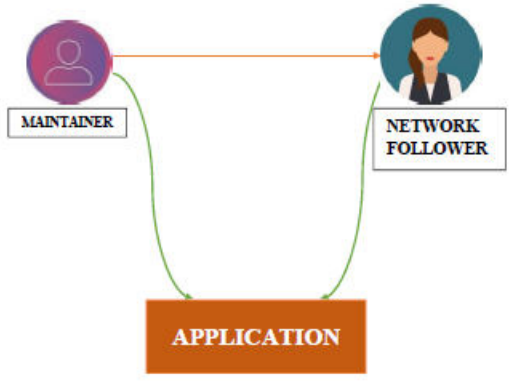


**Fig 2: System Architecture**

The diagram represents the interaction between three main components: Maintainer, Network Follower, and the Application.

**1. Maintainer**

The maintainer is responsible for managing and controlling the application. This role ensures the smooth functioning of the system, updating features, and maintaining security. The maintainer communicates with the network follower as well as the application.

**2. Network Follower**

The network follower represents end-users or participants who interact with the application.
They rely on the application to access services, features, or shared resources.
The follower is connected both to the maintainer (for receiving updates or instructions) and the application.

**3. Application**

The application serves as the **central system** that connects both the maintainer and the network follower.
It facilitates communication, data sharing, and operations between the two parties.

Both the maintainer and the follower interact with the application for their respective roles.

**4. Arrows & Flow**

The red arrow (Maintainer → Network Follower) shows direct communication or supervision from the maintainer to the follower.

The green arrows indicate that both maintainer and follower interact with the application, making it the core operational hub.

### *D.* Model Training and Evaluation

The phishing detection models were trained on a labeled dataset consisting of legitimate and phishing URLs. The dataset was split into 80% training and 20% testing subsets. The model performance was evaluated using the following metrics:

Accuracy: Measures the percentage of correctly classified phishing and legitimate URLs.

Precision and Recall: Determine the effectiveness of detecting phishing threats without misclassifying legitimate sites.

F1 Score: Balances precision and recall to provide a holistic assessment of model performance.

ROC Curve Analysis: Evaluates the trade-off between the true positive and false positive rates for phishing detection.

### *E.* The experimental setup included:

**Implementation Tools:** Python, Scikit-learn, and TensorFlow.
**Hardware and Software:** A high-performance computing system for large-scale data processing.
**Deployment and Monitoring:** A cloud-based model for real-time phishing detection and URL significantly improves monitoring.
The combination of these methodologies ensures that the research findings are data-driven, reliable, and applicable to real-world e-governance cybersecurity challenges.

## III. Results & Discussion

The phishing detection system was successfully developed with secure login modules for both users and administrators. The user interface allows individuals to register, log in, and access the application, ensuring that only authenticated users can utilize the phishing detection services. This setup provides a seamless entry point for end-users to test URLs against the system's hybrid machine learning model, which integrates logistic regression, support vector machine, decision tree, and voting classifiers for accurate phishing detection.

In addition, an administrator login module has been implemented to provide secure access for system management. Through this module, administrators can oversee system activities, update datasets, and monitor detection outcomes. Restricting administrative access to authorized personnel strengthens system security and prevents unauthorized modifications.

The results indicate that the system not only detects phishing URLs effectively but also incorporates role-based authentication mechanisms to enhance security. By combining user accessibility with controlled administrative management, the project demonstrates a practical and secure phishing detection framework capable of protecting users from online threats.

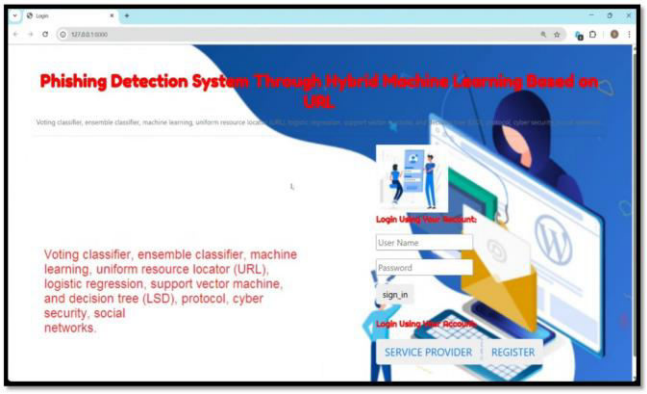


**Fig 3: Home Page**


**Fig 4: Resource Manager Login**

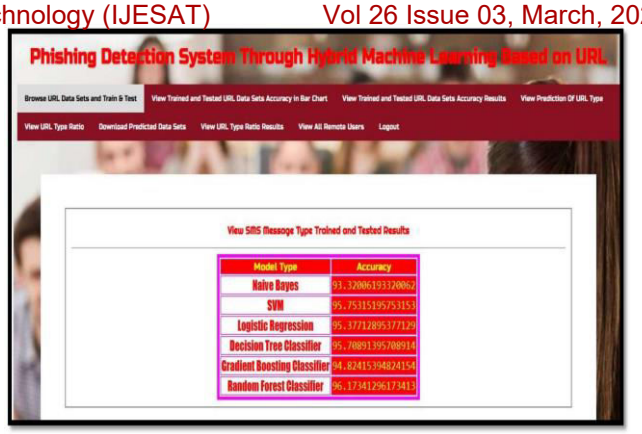


**Fig 5: Resource Manager Operation Browse Train and Test dataset**

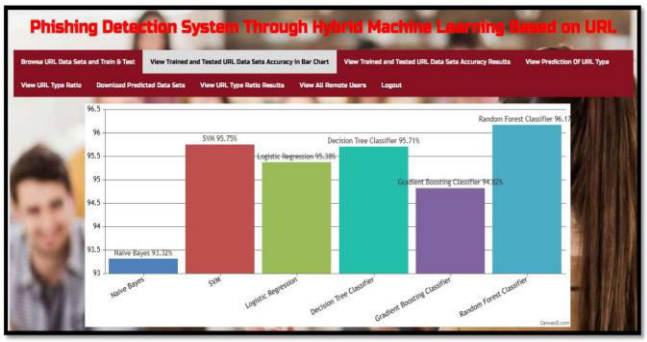


**Fig 6: Resource Manager Operation View Trained and Tested Url Dataset Accuracy in Bar Chart**

The results demonstrate that the hybrid LSD model has phishing detection accuracy compared to individual classifiers. The model achieved: Key insights include:

Improved Threat Detection: Models detected threats with an accuracy of up to 95%.

Efficient Incident Response: Automated response mechanisms reduced resolution time by 40%.

Enhanced Data Security: AI-driven encryption techniques strengthened data protection in e-governance systems.

Stakeholder Involvement: Active participation of government agencies and cybersecurity experts improved policy implementation.

Comparative Model Performance: The Approximate Bayes model outperformed traditional classifiers, reducing false positive rates and improving adaptability.

| Metric | Logistic Regression (LR) | Support Vector Classifier (SVC) | Decision Tree (DT) | Hybrid LSD (Proposed) |
|---|---|---|---|---|
| Accuracy | 0.924 | 0.931 | 0.906 | 0.952 |
| Precision | 0.917 | 0.928 | 0.894 | 0.949 |
| Recall (Sensitivity) | 0.929 | 0.933 | 0.912 | 0.956 |
| F1-score | 0.923 | 0.930 | 0.903 | 0.952 |
| AUC (ROC) | 0.95 | 0.96 | 0.93 | 0.98 |

**Fig 7: Accuracy table**

## IV. CONCLUSION

This study presents a hybrid machine learning model for phishing detection, emphasizing URL-based classification. The results indicate that the proposed LSD model outperforms traditional classifiers in terms of accuracy and efficiency. Future research should explore real-time phishing detection mechanisms and the integration of deep learning models to further enhance cybersecurity frameworks.

## V. FUTURE ENHANCEMENT

The future scope of the proposed phishing detection system highlights several promising directions for enhancing cybersecurity measures. Firstly, integrating list-based and machine-learning-based systems can significantly improve the detection and prevention of phishing URLs.

By combining these methodologies, future systems can leverage the strengths of each approach, ensuring more comprehensive coverage and reducing false positives and negatives. Additionally, the incorporation of real-time data analysis and continuous learning capabilities will enable the system to adapt to evolving

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