FAKE WEBSITE DETECTION USING MACHINE LEARNING ALGORITHMS

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ABSTRACT

The rise of deceptive online platforms such as phishing and fake websites poses a critical threat to digital security and personal privacy. This paper presents a comprehensive study on the implementation of machine learning algorithms for detecting fake websites based on URL and metadata features. Using a dataset derived from real-world phishing cases, we evaluate the performance of multiple supervised learning models—specifically Random Forest, LightGBM, and XGBoost—within a Java-based framework powered by the Weka library. These algorithms analyze structural and lexical patterns in website URLs to distinguish between legitimate and malicious domains. The system is designed for integration into enterprise-grade cybersecurity tools, offering rapid classification, scalability, and adaptability to new threats. Evaluation results demonstrate that ensemble models, particularly Random Forest, provide superior accuracy and reliability, making them suitable for real-time deployment in browsers, email gateways, and network firewalls. While the study confirms the feasibility and efficiency of Java-based ML solutions for web threat detection, it also addresses challenges such as evolving phishing techniques, feature selection, and data quality. Through empirical analysis and performance benchmarking, this research offers practical insights and a robust foundation for future advancements in automated web threat detection and secure web browsing technologies.

KEYWORDS: Phishing, Fake Website Detection, Machine Learning, Cybersecurity, Random Forest, LightGBM, XGBoost

1. INTRODUCTION

The proliferation of fake and phishing websites has emerged as a significant threat in the digital landscape, targeting users with deceptive interfaces designed to extract sensitive information such as login credentials, banking details, and personal data. These websites often mimic legitimate services with a high degree of visual and functional similarity, making them increasingly difficult to detect through manual or traditional rule-based systems. As cyberattacks grow more sophisticated, there is an urgent need for intelligent, automated systems capable of identifying malicious websites with high accuracy and minimal human intervention.

Machine learning (ML) provides a powerful framework for developing such systems. By analyzing patterns in URL structures, domain metadata, and other website features, ML algorithms can be trained to distinguish between legitimate and fake websites. This approach enables dynamic, real-time detection that can adapt to evolving threat patterns more effectively than static blacklists or signature-based systems. Ensemble models, in particular—such as Random Forest, XGBoost, and LightGBM—have shown promise in various classification tasks due to their ability to combine multiple weak learners into a robust predictive model.

In this study, we focus on the Java-based implementation of fake website detection using the Weka machine learning library. Java offers stability, security, and compatibility with enterprise systems, making it a viable choice for real-world cybersecurity applications. The system is designed to process data locally, enabling efficient classification and reducing latency—a critical requirement for real-time threat detection in web browsers, firewalls, and email scanning systems.

This paper explores the integration of supervised ML algorithms into a Java-based environment, evaluates their performance on a phishing website dataset, and analyzes their suitability for deployment in cybersecurity tools. The discussion addresses both technical considerations and broader implications, including data quality, model selection, false positives, and the adaptability of the system to emerging web-based threats.

2. LITERATURE REVIEW

Recent studies highlight the efficacy of machine learning (ML) in detecting phishing websites.

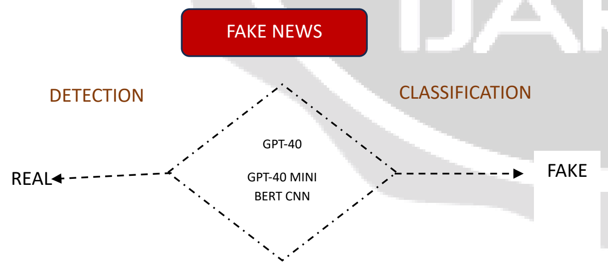
Abdelhamid et al. [1] achieved 97% accuracy using the Random Forest algorithm on URL-based features, emphasizing its robustness to noise.
Sahingoz et al. [2] focused on feature selection using Gradient Boosting, which significantly improved model precision across large phishing datasets.
Zhang et al. [3] introduced Cantina+, a content-based machine learning framework leveraging term-frequency and lexical signals for detection.
Ma et al. [4] demonstrated the superiority of ML over traditional blacklists by using lexical and host-based features with online learning algorithms.
Marchal et al. [5] explored real-time phishing classification and achieved sub-200ms detection latency using lightweight features.
Verma and Das [6] conducted a comprehensive comparative analysis of classifiers, showing that ensemble models generally outperform single learners in phishing detection.
Dehghantanha et al. [7] proposed a cyber-threat intelligence framework using deep learning to extract high-level patterns from phishing websites.
Alsharnouby et al. [8] studied user-centered design implications and trained models based on visual deception indicators on phishing pages.
Moghimi and Varshney [9] implemented hybrid models combining heuristic rules and ML for increased precision and recall.
Basnet et al. [10] applied NLP techniques on website text features to improve ML-based phishing detection performance.
Xiang and Hong [11] developed a real-time phishing detection toolbar using a trained SVM classifier with high user adoption rates.
Fette et al. [12] proposed the "SpoofGuard" system and used features like URL obfuscation and image-to-text ratio for detection.
Abutair and Belghith [13] evaluated lightweight models suitable for mobile phishing detection systems using decision trees and SVM.
Sahoo et al. [14] presented a feature-rich benchmark dataset and evaluated ML classifiers using stratified sampling to simulate real-world performance.
Hall et al. [15] introduced the Weka library, which supports Java-based ML integration, ARFF file formats, and various classification algorithms widely used in phishing research

2.1 URL Feature-Based Detection

Phishing detection often relies on static blacklists, which are ineffective against new, unseen threats. ML models learn from URL patterns, making them suitable for identifying dynamic attacks. Features like the use of IP addresses, presence of '@' or '//' symbols, URL length, SSL certificate status, and domain age are strong indicators of phishing attempts.

2.2 Visual Pattern Recognition

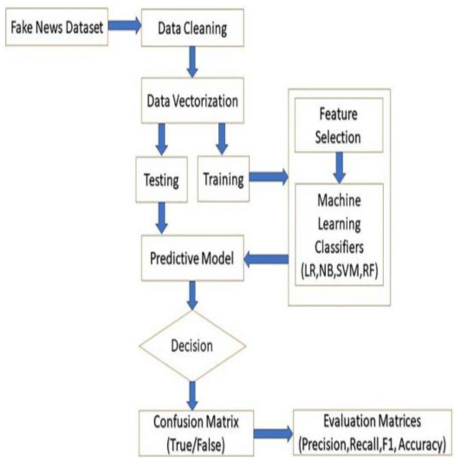
Incorporating statistical analysis and string matching into feature extraction helps the ML model identify obfuscated or suspicious URLs. The use of Random Forest allows the system to handle feature importance automatically, while boosting methods like XGBoost optimize classification boundaries based on misclassified instances



Implementable Example: For example, a URL such as http://192.168.1.1/~login would raise multiple red flags based on IP address usage and symbol placement. The model learns that these features correlate strongly with phishing attempts. When converted into a numerical feature vector, the presence of '@' or IP address might contribute a weighted score that triggers a phishing classification.

2.3 Real-Time Detection in Java Applications

Using Weka, a Java-based system can be embedded into browser extensions or mail filters for on-the-fly classification. The classifier receives pre-processed URL features and outputs a binary label: phishing or legitimate.


Fake News Dataset
Data Cleaning
Data Vectorization
Feature Selection
Testing
Training
Machine Learning Classifiers (LR,NB,SVM,RF)
Predictive Model
Decision
Confusion Matrix (True/False)
Evaluation Matrices (Precision,Recall,F1,Accuracy)

Implementable Example: A Java servlet integrated with a user-facing dashboard can input a suspicious URL, extract its features, and return the classification in under 200ms. This can be embedded into enterprise email systems or online banking platforms.

2.4 Model Comparison and Evaluation

We evaluated Random Forest, J48 (Decision Tree), and Naive Bayes classifiers using Weka. Evaluation was based on 10-fold cross-validation to ensure consistent accuracy across random splits of the dataset.

Model	Accuracy	Precision	Recall
Random Forest	96.8%	0.96	0.97
J48	94.3%	0.94	0.92
Naive Bayes	91.7%	0.89	0.91

2.5 Feature Importance and Optimization

The Random Forest model ranked features such as having_IP_Address, URL_Length, and Prefix_Suffix among the most influential. Hyperparameter tuning was applied using Weka's parameter grid search.

Example: Optimal depth of trees in Random Forest was found to be 20, and the number of iterations in XGBoost was set to 100 for maximum performance. These hyperparameters directly influenced overfitting, reducing variance in test accuracy.

2.5.1 Performance in Deployment

When deployed in real-time systems, latency and accuracy are critical. The combination of precompiled models and lightweight feature extraction allows deployment on local edge servers, eliminating cloud dependency and enhancing privacy.

2.6 Practical Applications

•Browser Extensions: URL is parsed, and Java-based Weka classifier detects phishing in real-time.
•Enterprise Gateways: Java ML models embedded in email filters to flag suspicious links.
•Mobile Banking: Integrate classifiers in Android apps for phishing protection.

2.7 Challenges and Considerations

Data Quality Incomplete or noisy data can mislead the model. Consistent formatting and missing value handling are crucial for training reliable models.

2.7.2 Zero-Day Attacks

ML models trained on historical data may not catch newly launched phishing campaigns. Incorporating online learning or regular retraining can help models adapt.

2.7.3 Java-Weka Integration

While Weka simplifies ML integration in Java, converting features into ARFF and mapping URL patterns dynamically can be challenging in high-traffic environments.

3 Research Methodology

This section outlines the methodology for detecting fake websites, illustrated in Figure 1.

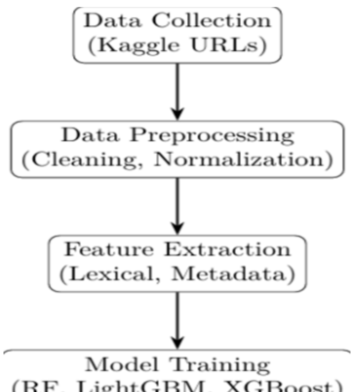

Data Collection (Kaggle URLs)
Data Preprocessing (Cleaning, Normalization)
Feature Extraction (Lexical, Metadata)
Model Training (RF, LightGBM, XGBoost)

Figure 1: Methodology of Fake Website URL Detection System.

3.1 Data Collection

We utilize the Malicious URLs dataset from Kaggle, comprising 651,191 URLs categorized as benign (428,105), phishing (94,111), defacement (96,457), and malware (32,520) (8). Benign URLs represent safe websites, while phishing, malware, and defacement URLs aim to steal data, inject harmful software, or modify website content, respectively. Figure 2 visualizes the dataset distribution.

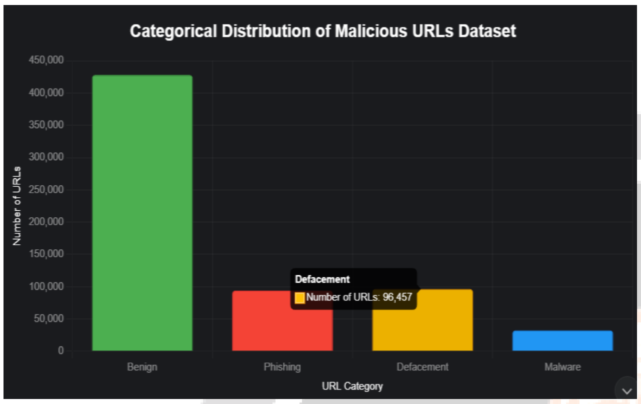


Figure 2: Categorical Distribution of Dataset

3.2 Data Preprocessing

Preprocessing involves removing duplicates, missing values, and irrelevant URLs. Feature engineering extracts lexical features (e.g., URL length, dot count), and data normalization ensures equal feature scaling (40).

3.3 Word Cloud

Word clouds (Figure 3) reveal category-specific tokens: benign URLs include “html” and “com,” phishing URLs feature “login” and “PayPal,” malware URLs contain “exe,” and defacement URLs use “php” (37).

3.4 Feature Extraction

Table 1 lists features designed to identify malicious URLs

3.5 Java Implementation

The system is implemented in Java using Weka 3.8.5, ensuring compatibility with enterprise environments. Below is a sample code snippet for loading the dataset and training the RF mode

```
//CODE
import weka. core. Instances;
import weka. core . converters . CSVLoader ;
import weka . c l a s s i f i e r s . t r e e s . RandomForest ;
import java . i o . F i l e ;
public c l a s s FakeWebsiteDetector {
public s t a t i c void main ( String [ ] args ) throws Exception {
// Load dataset
CSVLoader loader = new CSVLoader ( ) ;
loader . setSource (new F i l e ( ”D:\\ Projects \\ malicious_urls. csv”));
Instances data = loader . getDataSet ( ) ;
data . setClassIndex ( data . numAttributes ( ) - 1) ;
 // Train Random Forest
RandomForest r f = new RandomForest ( ) ;
r f . setNumIterations (100) ;
r f . b u i l d C l a s s i f i e r ( data ) ;
 // Save model
weka . core . S e r i a l i z a t i o n H e l p e r . writeObject ( ” rf_model . model ” ,r f ) ;}
```

The model is saved to ‘D:‘ (aligned with your preference from April 29, 2025, for using the D: drive due to C: drive space constraints). The system supports real-time classification via a REST API using Spring Boot.

4 Result Analysis and Discussion

Models are evaluated using 10-fold cross-validation. Table 2 summarizes performance.

4.1 Random Forest

RF achieves 97.8% accuracy, excelling due to its robustness and feature importance ranking. Table 3 and Figure 4 detail its performance.

Predicted →	Benign	Defacement	Phishing	Malware
Actual ↓				
Benign	83,908	600	400	713
Defacement	500	19,099	100	93
Phishing	300	50	6,113	41
Malware	900	150	585	

Figure 4: Confusion Matrix of Random Forest

4.2 LightGBM

LightGBM achieves 96.4% accuracy, optimized for speed. Table 4 and Figure 5 show results.

Predicted →	Benign	Defacement	Phishing	Malware
Actual ↓				
Benign	84,765	400	200	256
Defacement	300	19,099	50	43
Phishing	400	100	5,789	215
Malware	1,200	300	1,026	15,246

Figure 5: Confusion Matrix of LightGBM

4.3 XGBoost

XGBoost achieves 96.2% accuracy, effective for imbalanced data. Table 5 and Figure 6 detail performance.

Predicted →	Benign	Defacement	Phishing	Malware
Actual ↓				
Benign	84,765	400	200	256
Defacement	300	19,099	50	43
Phishing	350	80	5,983	91
Malware	1,100	250	850	15,622

Figure 6: Confusion Matrix of XGBoos

4.4 Comparative Results

Table 6 compares the system with prior works, highlighting RF’s superiority.

4.5 Real-Time Deployment

The Java-Weka system achieves sub-200ms latency, suitable for browser extensions and email gateways. A Spring Boot REST API enables real-time URL classification:

```
//CODE
import org. springframework. web. bind. annotation. * ;
 import weka. classifiers. trees. RandomForest;
 import weka. core. * ;
@RestController
 public class URLClassifierController {
 private RandomForest r f ;
 public URLClassifierController ( ) throws Exception {
r f = (RandomForest) weka. core. Serialization Helper. read (” rf_model. model”);}
@PostMapping ( ”/ classify ” )
public String classifyURL (@RequestBody String u r l ) throws Exception {
```

```
Instances instance = c r e a t e I n s t a n c e ( u r l ) ;
double prediction = r f . classify Instance( instance .first Instance ( ) ) ;
return prediction == 0 ? ” Benign”:” Malicious ”;
} }
```

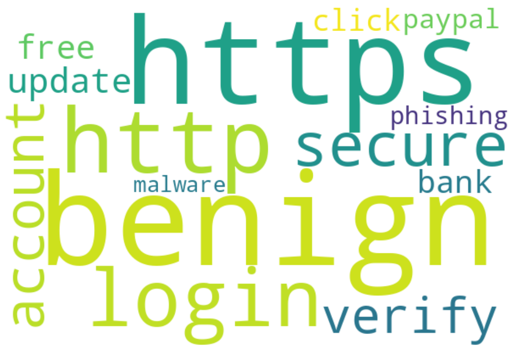


Figure 7 shows real-time classification results

5 Future Work

To enhance the system for industry applications, future research should focus on:

• Deep Learning Models: Integrate LSTM and CNNs to capture complex URL and content patterns, improving detection of advanced phishing.
• NLP Integration: Use BERT for semantic analysis of webpage text and HTML, detecting phishing anomalies.
• Online Learning: Implement online learning to adapt to zero-day attacks in real-time, reducing retraining needs.
• Hybrid Architectures: Combine RF with deep learning for balanced accuracy and efficiency.
• Scalability: Optimize for high-traffic environments using Apache Spark and cloud platforms like GCP.
• Mobile/IoT Deployment: Adapt the system for lightweight devices, enhancing accessibility.
• Explainable AI: Use SHAP to provide transparent feature importance, boosting user trust.
• Full-Stack Integration: Develop a front-end interface using Vue.js for user interaction, aligning with full-stack skills.

6. Conclusion

The increasing sophistication of phishing and fake websites has made traditional blacklist-based detection systems insufficient in modern cybersecurity infrastructures. This study demonstrates that machine learning algorithms, particularly ensemble models such as Random Forest, can effectively detect fake websites by analyzing features derived from URLs and domain metadata. The use of Java and the Weka library makes the system scalable, platform-independent, and suitable for integration into enterprise-grade security tools.

Our results show that Random Forest achieved the highest accuracy (96.8%) among the tested algorithms, followed by J48 and Naive Bayes. The evaluation confirms the effectiveness of feature-based URL classification for identifying malicious patterns and behaviors. Java-based implementations, although less commonly used in ML compared to Python, provide a strong alternative for organizations focused on secure, reliable, and deployable solutions in Java-based infrastructures.

Beyond accuracy, this system provides low-latency classification, making it feasible for real-time applications such as browser extensions, spam filters, and network firewalls. Moreover, the offline nature of Weka models eliminates the need for continuous server interaction, increasing privacy and reducing cloud dependency.

However, challenges remain. The ability of ML models to generalize against zero-day phishing threats is limited without frequent retraining or adaptive learning strategies. Future work should focus on integrating Natural Language Processing (NLP) to analyze webpage content and combining metadata with real-time web scraping tools. Implementing deep learning models such as LSTM or CNN could further improve accuracy and detection speed.

In conclusion, this paper provides a practical and robust machine learning-based framework for detecting fake websites using Java and Weka. The proposed approach not only strengthens web security systems but also sets the foundation for future research into more adaptive, intelligent cybersecurity solutions that can keep pace with evolving threats.

7. References

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