



# Phishing Website Classification

## (Data Mining Project)

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### Introduction

Phishing is a deceptive online practice where attackers impersonate legitimate entities to steal sensitive information. It causes significant financial and reputational damage to individuals and organizations

Traditional methods of phishing detection, such as blacklisting and manual inspection, are often inadequate

This project explores the potential of machine learning to automate phishing website detection and improve accuracy

### Objective

To identify the most influential features and build models with high accuracy to assist in automated phishing detection systems.

### Methodology

#### Data Preprocessing

- Selected the most impactful features using domain specific knowledge.
- 15 attributes dropped and 14 attributes kept.

- Load ARFF file using liac-arff library.
- Convert data to pandas DataFrame.

#### Feature Selection

- Training Testing dataset division(75%, 25%)
- Train classification models: Decision Tree, K-Nearest Neighbors.
- Optimize model parameters using cross-validation.

#### Model Building

- Evaluate performance using:
- Accuracy
  - Confusion Matrix
  - Classification Report

#### Model Evaluation

- SSL certificate (Secure Sockets Layer) is one of the most critical factors .
- A secure and valid SSLfinal\_State suggests that the website is likely to be legitimate.
- A missing, invalid, or suspicious SSLfinal\_State strongly signals a phishing attempt.

### Dataset and Features



- Source :** [UC Irvine Machine Learning Repo](#)
- Size :** dataset of 11,056 web URLs with lexical and security features
- Key Attributes :** SSLfinal\_State, URL\_Length, annd web\_traffic
- Lexical:** URL Length, having\_IP\_Address, having\_At\_Symbol, double\_slash\_redirecting, HTTPS\_token.
- Host-based:** SSLfinal\_State, Domain\_registration\_length, age\_of\_domain, DNSRecord.
- Content-based:** Request\_URL, URL\_of\_Anchor, SFH, popUpWidnow, web\_traffic
- Irrelevant features** like Shortining\_Service, Prefix\_Suffix were dropped to prevent data leakage and overfitting, ensuring better model generalization.

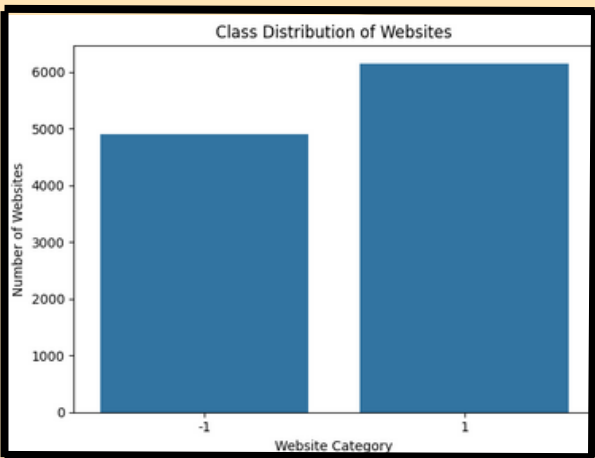


Figure 1. Count of Phishing vs Non Phishing Websites

here -1 indicates Phishing websites and 1 indicates Non-Phishing based websites

### Results

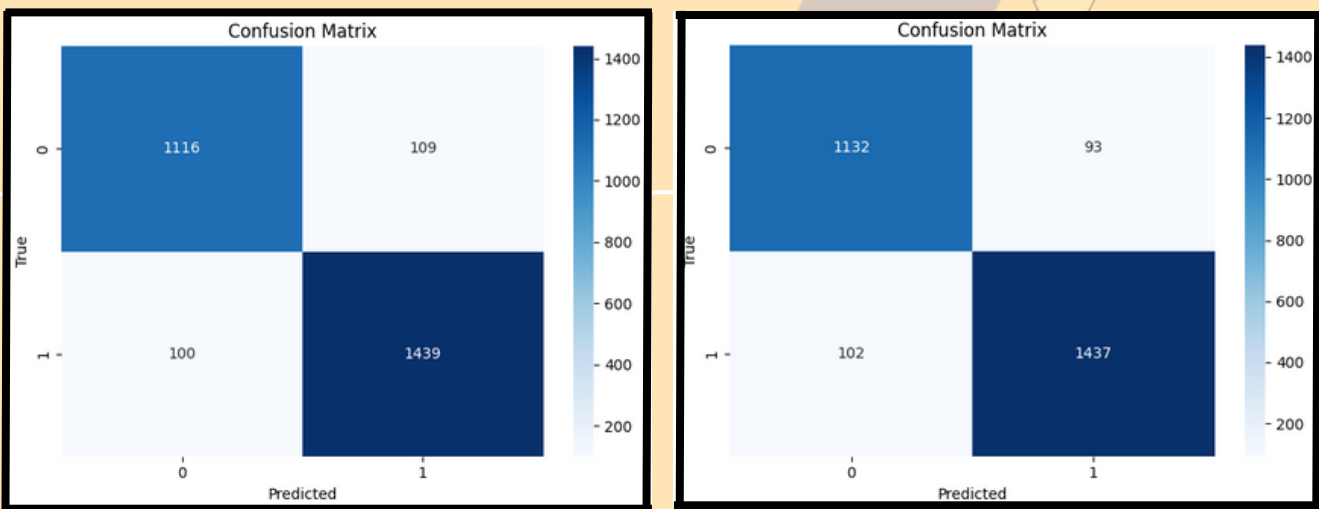


Figure 2. Confusion Matrix of (a) knn vs (b) decision tree model

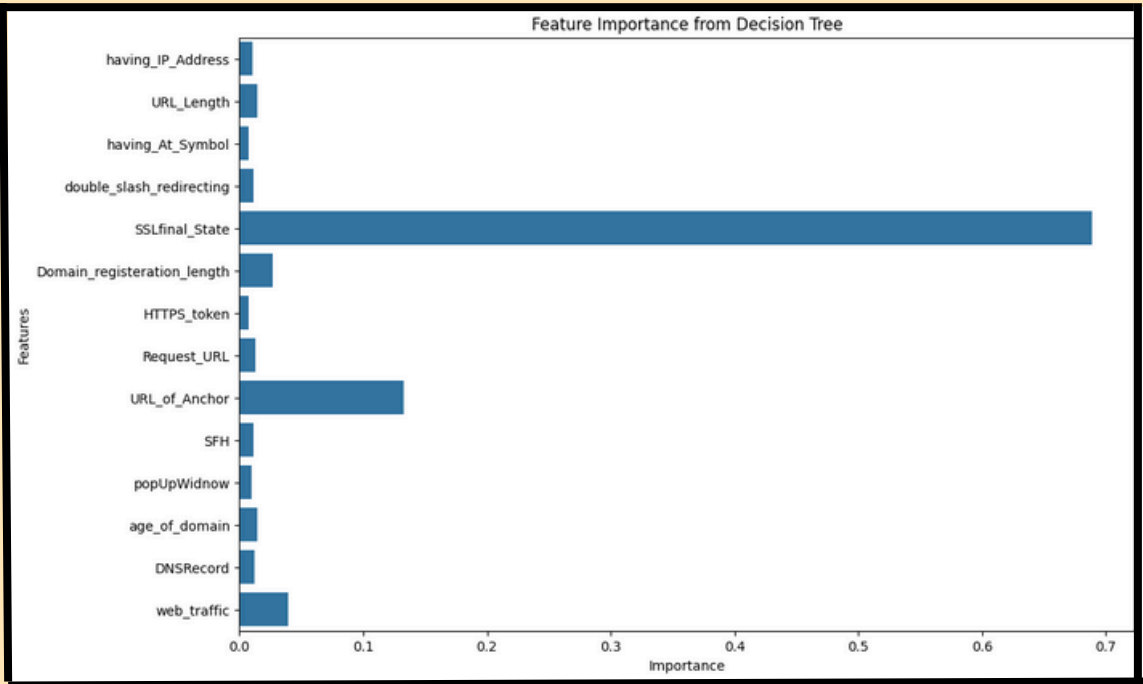


Figure 3.Feature importance using decision tree

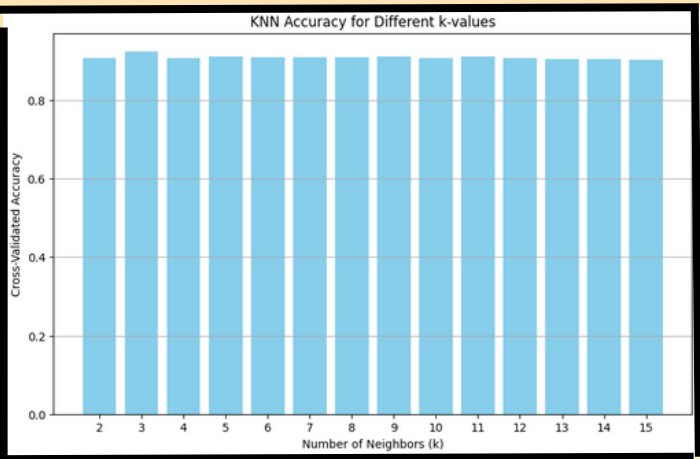


Figure 4: knn accuracy for k values

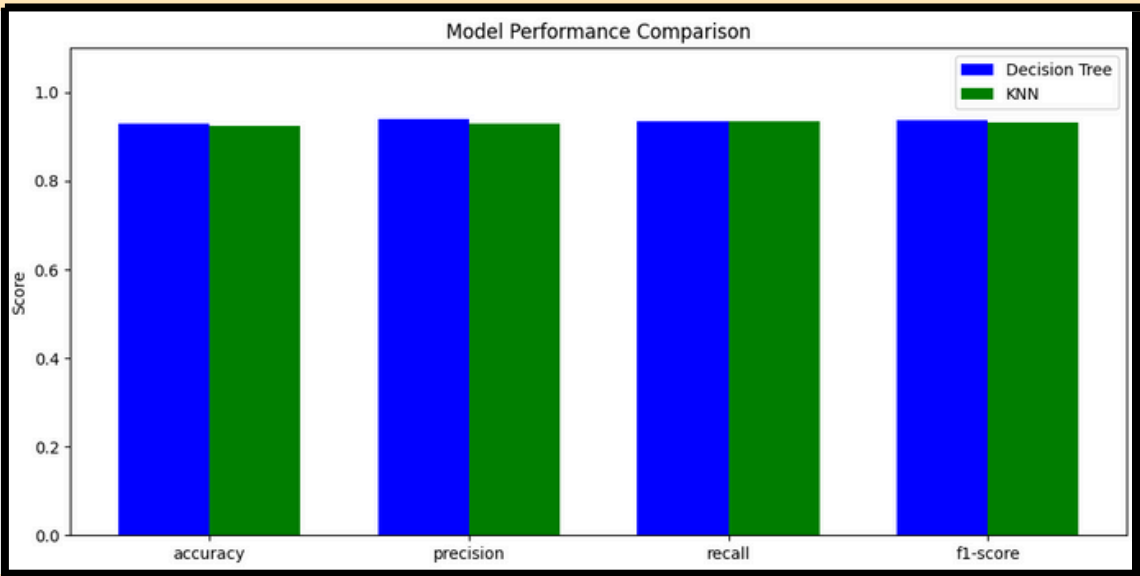


Figure 5. Model performance comparison

### Conclusion

- Manually identified influential features for phishing website detection.
- Both the Decision Tree and KNN models perform well, achieving comparable accuracies of 92.94% and 92.43%, respectively.
- Demonstrated the potential of automated systems for phishing detection.

### References

1. Tan P.N., Steinbach M, Karpatne A. and Kumar V. Introduction to Data Mining, Second edition, Sixth Impression, Pearson, 2023.