

Malicious URL Detector

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Goal Definition

Drive-By Downloads

Execute malicious code on the victim's system

Malware Distribution

Host or redirect to sites that distribute malware

Phishing Attacks

Lead users to fake websites that mimic legitimate ones



Real-Time Protection

Identifying and blocking access to harmful URLs

Early Threat Detection

Preventing users from interacting with dangerous content

Reducing Attack Surface

Prevent potential entry points for cyberattacks

Common Characteristics of Malicious URLs

Misspelled Domain Names

Cybercriminals register domains that are intentionally similar to well-known websites

IP Addresses

Raw IP Addresses instead of domain names to bypass domain registration requirements

Long, Random Strings

Attempt to obfuscate the true purpose of the URL

Unusual Characters

Used to confuse users or evade detection

Lack of HTTPS

Phishing sites may not have valid SSL certificates (HTTPS)

Overuse of Subdirectories

A technique to obscure the final destination



Data Gathering



PhishTank

PhishTank

Data and information about phishing on the Internet.

Kaggle

Platform for data science competitions

kaggle

Data Pre-Processing



01 - Data Cleaning

Identifying and correcting errors, inconsistencies and inaccuracies

02 – Class Balancing

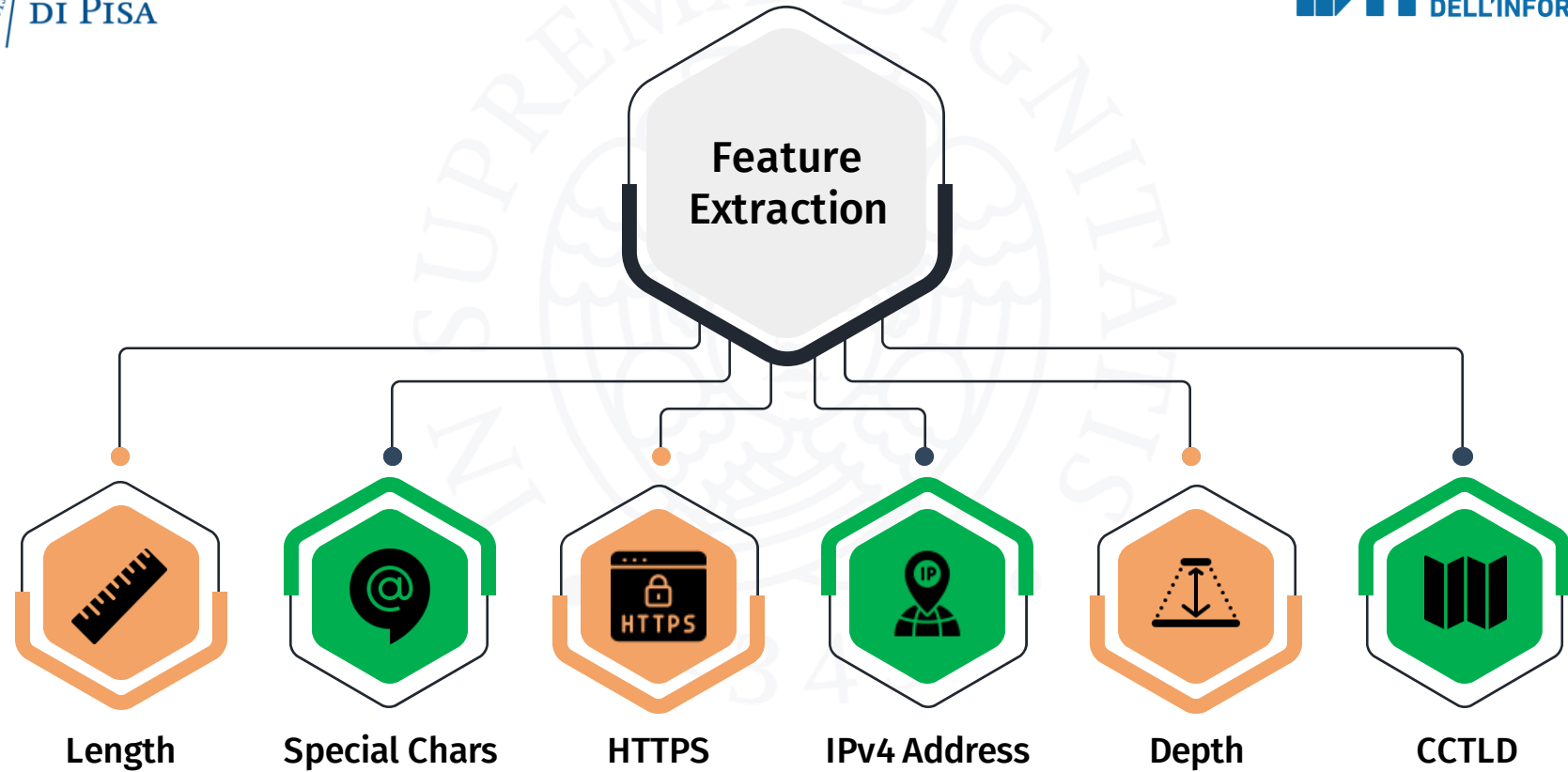
As imbalancing can lead to biased model and misleading accuracy

03 – Feature Extraction

Enhancing the model's ability to learn patterns in the data

04 – Heuristics

Comparison with some of the empirical rules found in literature



Heuristics Confrontation



Special Chars

'@' Symbol: 93.827%
'-' Symbol: 90.126%
'_' Symbol: 53.846%



IPv4 Address

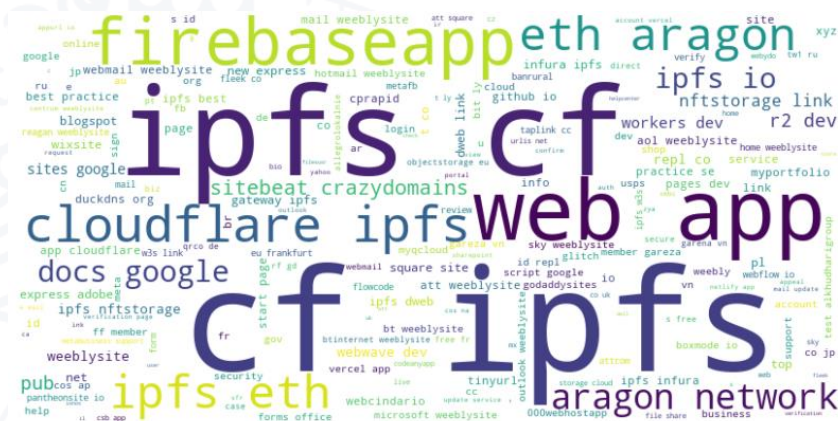
100% Malicious
URLs

Reference: Youness Mourtaji, Mohammed Bouhorma, Danyal Alghazzawi, Ghadah Aldabbagh, Abdulah Alghamdi, "Hybrid Rule-Based Solution for Phishing URL Detection Using Convolutional Neural Network".

Preliminary Data Exploration



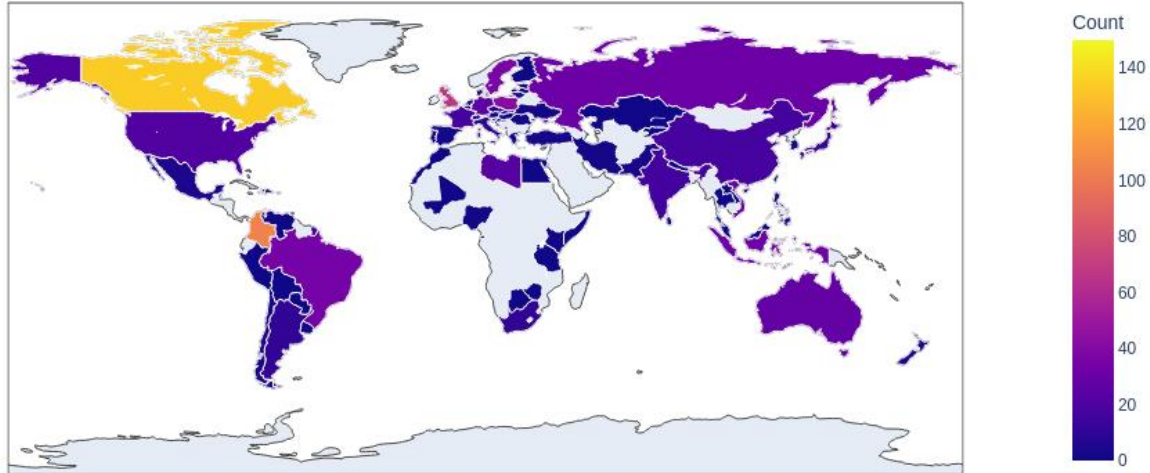
Benign



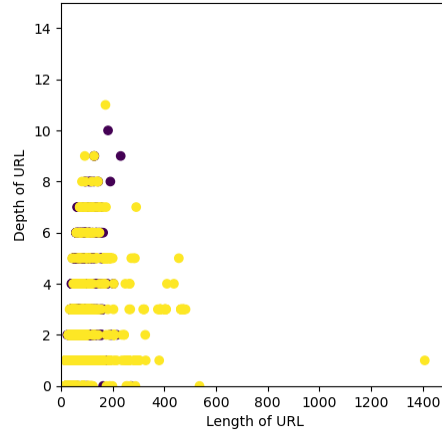
Malicious

Preliminary Data Exploration

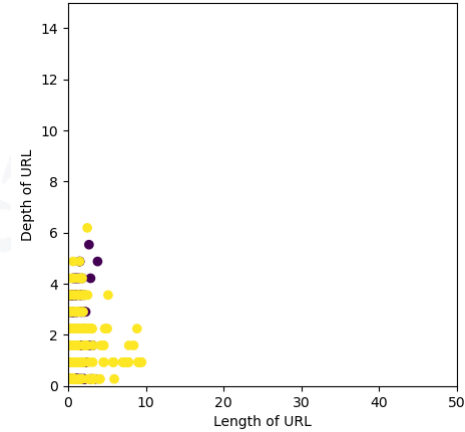
Distribution of Country-Code Top Level Domains



Normalization process



Z-Score



Data Mining



**Decision Tree
Classifier**



**Random Forest
Classifier**



**Logistic
Regression**

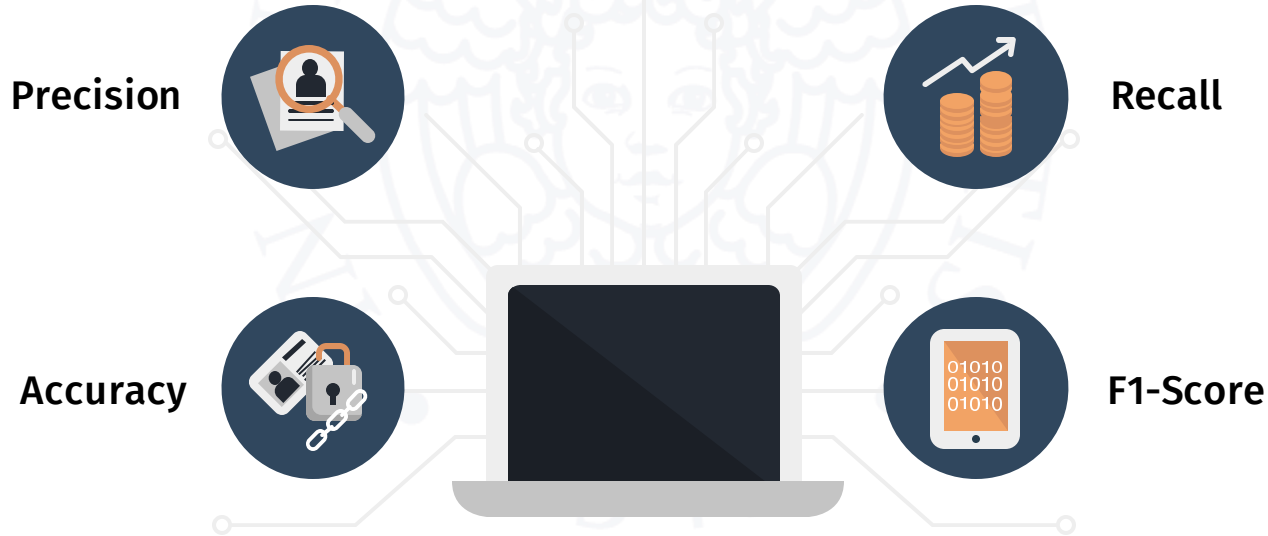


**Gaussian Naive
Bayes**

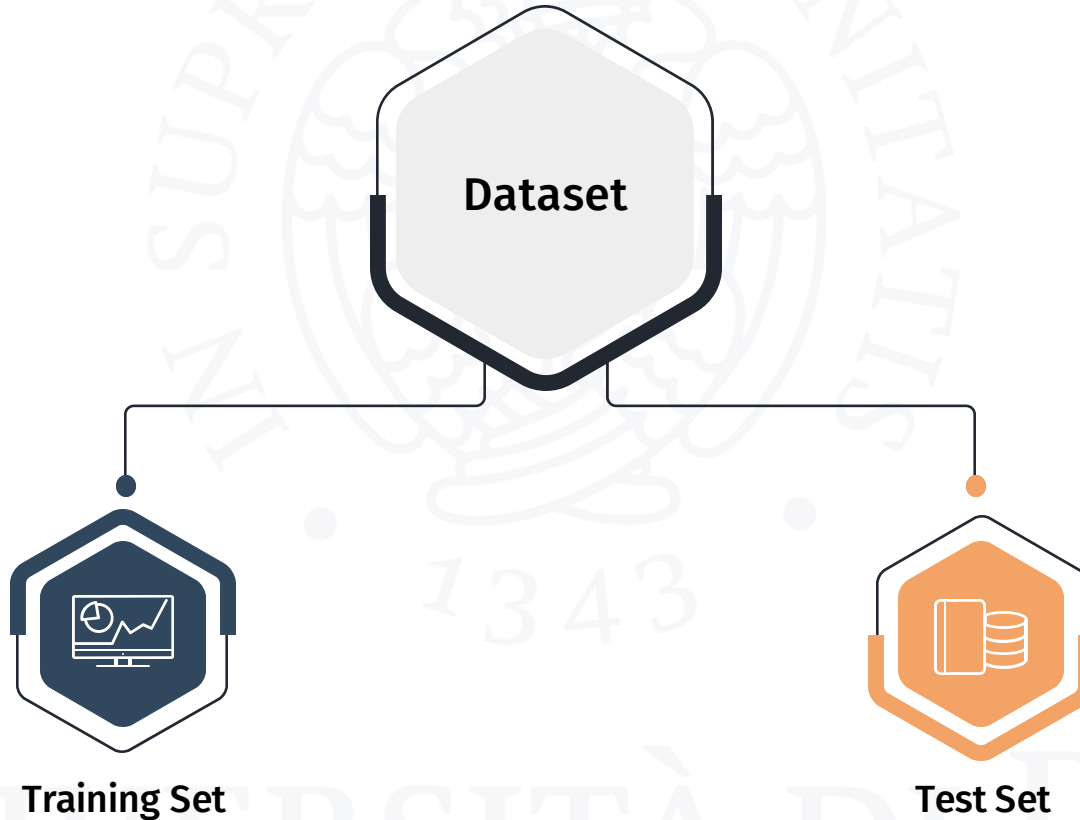


Linear SVC

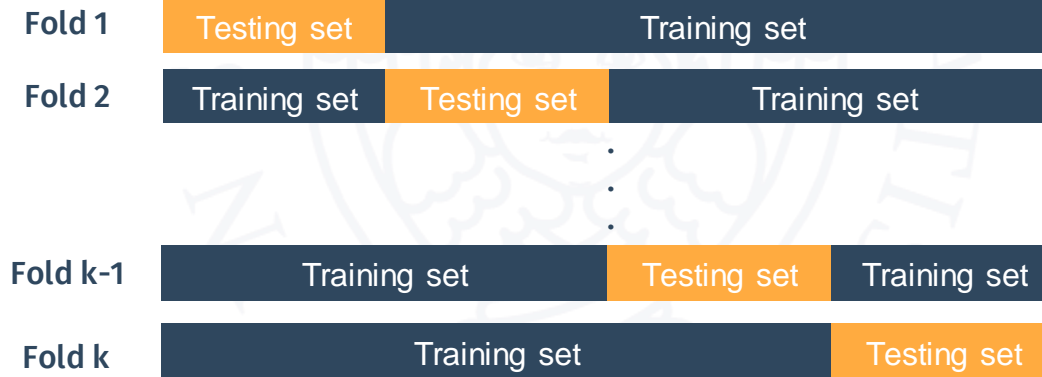
Performance Evaluation



Holdout Method

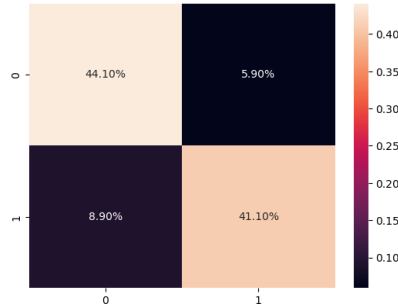


Stratified K-Fold



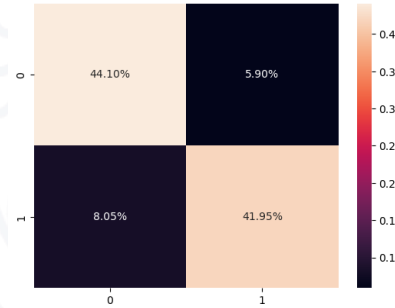
Results – Hold out

Decision Tree
Classifier



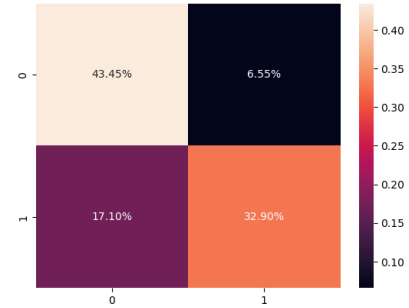
85.20%

Random Forest
Classifier



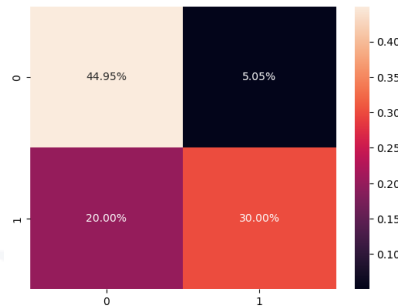
86.05%

Logistic
Regression



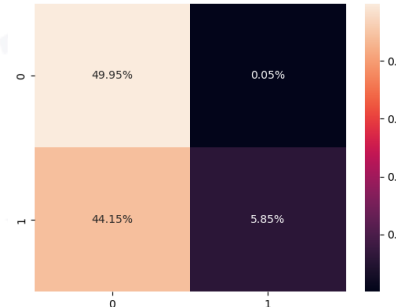
78.35%

Linear SVC



74.95%

Gaussian
Naive Bayes

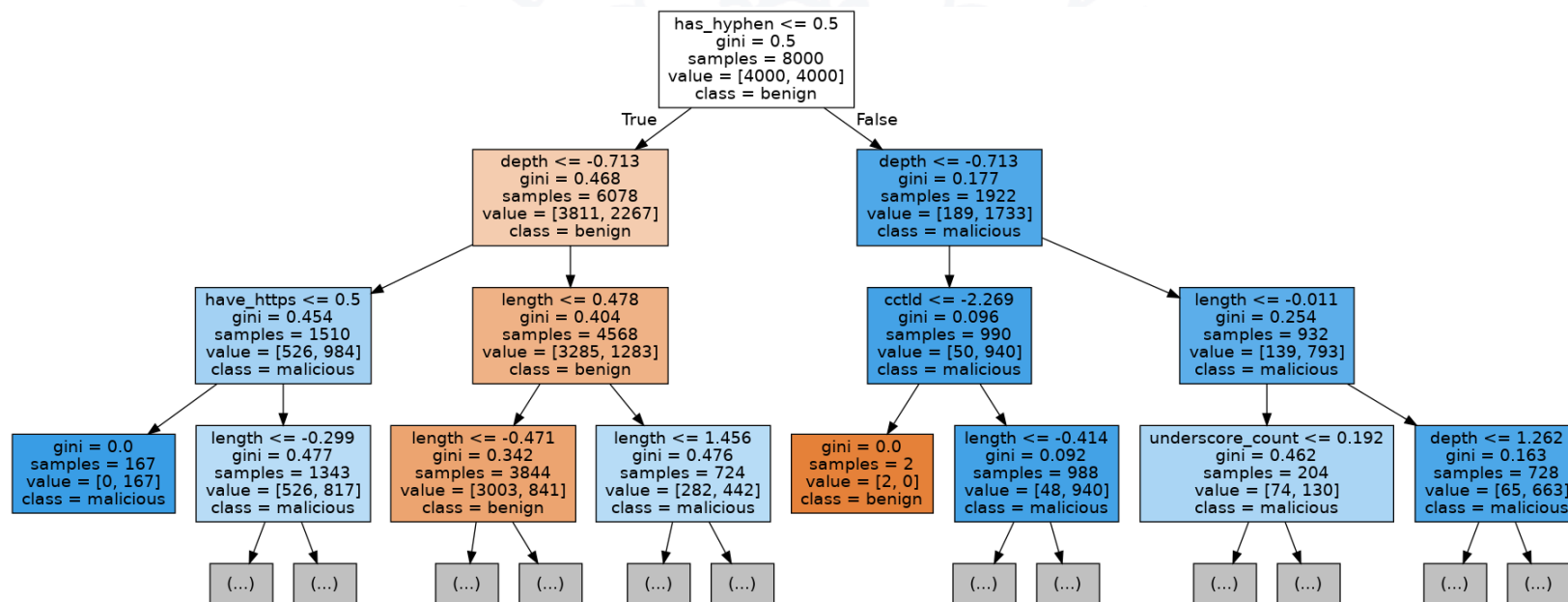


55.80%

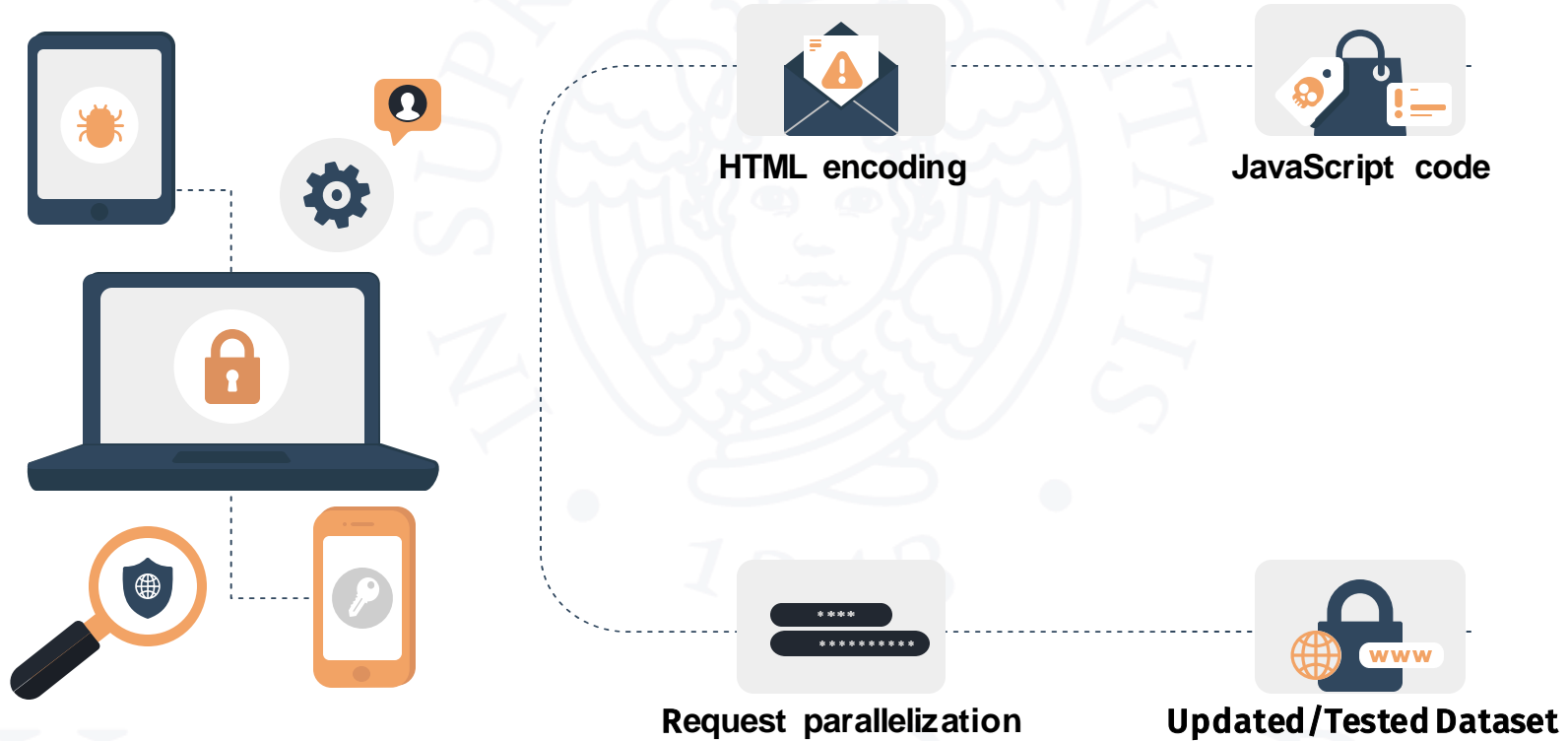
Results – Accuracy

	Model	Accuracy	Accuracy with SKF	Accuracy with Feature Selection
0	DecisionTreeClassifier	0.8520	0.842	0.7770
1	RandomForestClassifier	0.8605	0.852	0.7785
2	LogisticRegression	0.7635	0.736	0.6655
3	LinearSVC	0.7495	0.740	0.6700
4	GaussianNB	0.5580	0.561	0.5520

Decision Tree Representation



System Improvement





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Thanks For The Attention!