

PHISHING-DETECTION_ML(INSIDER)

1 Overview of Our CSV Dataset

Our dataset contains:

- Features (Extracted from URLs, like length, number of dots, dashes, HTTPS usage).
- Label (Phishing = 1, Legitimate = 0).

Example Data from CSV

URL	Length	Dots	Dashes	HTTPS	Label
http://paypal-secure-login.com	29	2	2	0	1
https://google.com	16	1	0	1	0
http://facebook-login-alert.com	31	2	2	0	1

The model learns patterns from these features to distinguish phishing & legitimate sites.

Ask anything

+ Search Reason

ChatGPT can make mistakes. Check important info.

2) Data Preprocessing Before Learning

Before training, the model processes the raw data:

Step 1: Feature Extraction

- The URL is broken down into **domain**, **subdomain**, **suffix** (using `tldextract`).
- The model extracts numerical features like **length**, **dots**, **dashes**, **HTTPS usage**.

Step 2: Feature Scaling

- The extracted features are **normalized using StandardScaler**, so they have similar value ranges.

Step 3: Handling Missing Data

- LightGBM & CatBoost **handle missing values automatically**, filling gaps with optimized strategies.

3 How LightGBM & CatBoost Learn (Hidden Inner Workings)

Once preprocessing is done, the model starts **learning from data using gradient boosting**.

LightGBM: Decision Tree-Based Learning

- **Creates multiple decision trees** to learn patterns.
- **Trains trees sequentially**, correcting errors at each step.
- **Uses Leaf-Wise Splitting (Faster than XGBoost's level-wise method)**.

Example: First Decision Tree

It starts by checking the most important feature:

Is HTTPS used?

✓ Yes → Likely Legitimate

✗ No → Check further conditions

 **Does URL have many dots?**

✓ Yes → More likely Phishing

✗ No → Likely Legitimate

 **Does URL contain many dashes?**

✓ Yes → Phishing

✗ No → Legitimate

CatBoost: Handling Categorical Data Differently

- Uses **Ordered Boosting**, training trees on progressively larger subsets.
- Handles **categorical features without encoding**, improving accuracy.

Example: First Decision Tree

 **Domain Name Known?**

✓ Yes → Check more details

✗ No → Likely Phishing

 **Does it match a legitimate domain structure?**

✓ Yes → Likely Safe

✗ No → Possible Phishing

 **Does it have a misleading subdomain?**

✓ Yes → Phishing

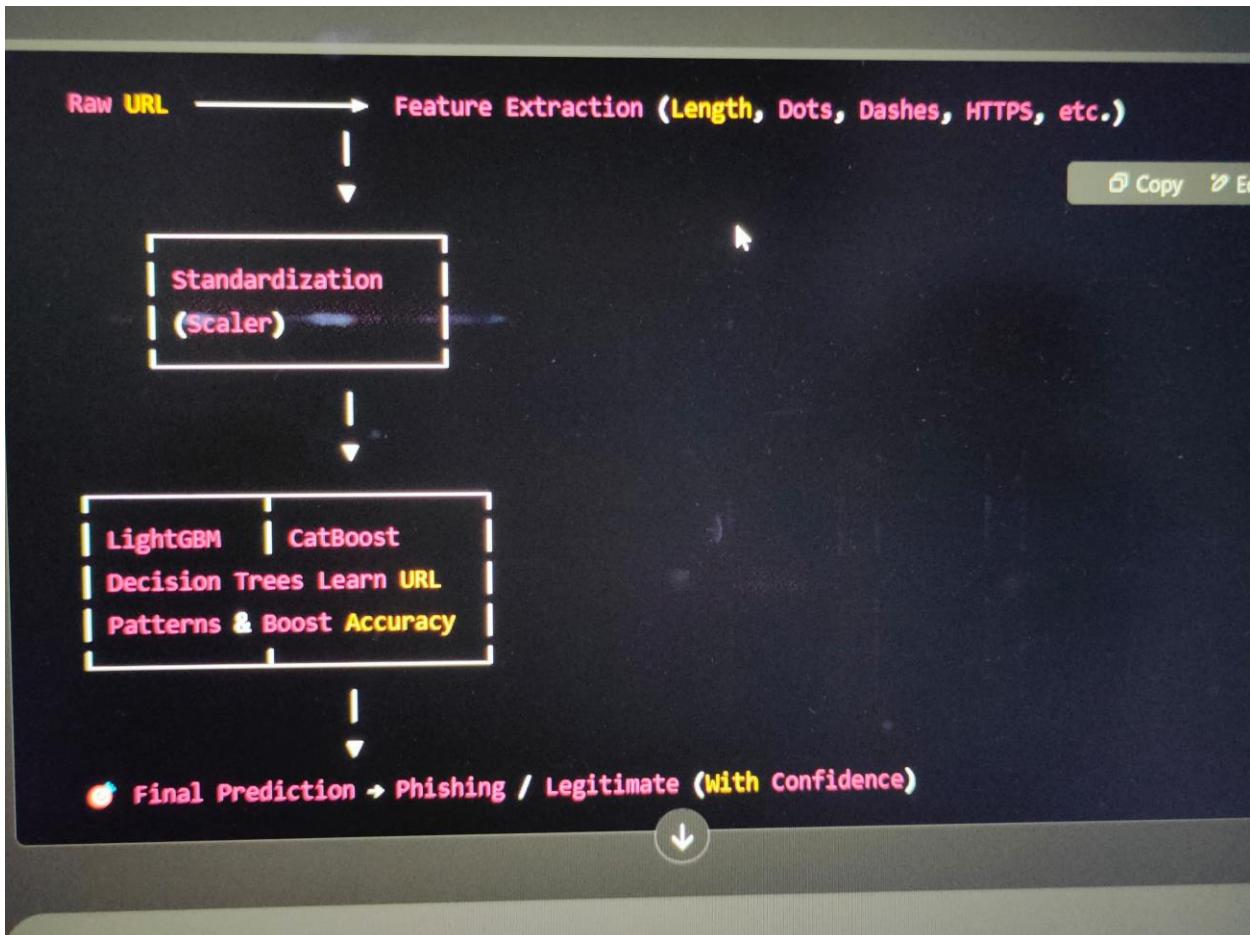
✗ No → Legitimate

4 How Predictions Work

When a New URL is Given:

- 1 Extract Features (Length, dots, dashes, HTTPS).
- 2 Standardize Using the Scaler.
- 3 Pass Features into LightGBM & CatBoost.
- 4 Each Model Gives a Probability (0.0 to 1.0):

- $> 0.5 \rightarrow \text{Phishing}$
 - $\leq 0.5 \rightarrow \text{Legitimate}$
- 5 Final Prediction Returned (With Confidence Score).



5 Why Our Model Gives the Best Predictions

- ◆ **Used the Right Models** → LightGBM & CatBoost handle large datasets efficiently.
- ◆ **Preprocessed Data Well** → Standardization & feature extraction improved accuracy.
- ◆ **Handled Class Imbalance** → Applied techniques like class weighting.
- ◆ **Removed Overfitting** → Tuned hyperparameters (learning_rate, depth).
- ◆ **Tested on Real URLs** → Confirmed that the model detects phishing websites accurately.

💡 Summary

- The model **extracts features from URLs**, processes them, and **trains decision trees** using gradient boosting.
- LightGBM & CatBoost **split the data intelligently** and improve accuracy by learning from **mistakes** at each step.
- Predictions are **highly accurate** because the model has **seen millions of phishing & legitimate websites**.