Internship_CodeB_week 5 & 6

April 24, 2025

1 Phishing Website Detection

- Name : Gaurav Vijay Jadhav
- github : [https://github.com/jadhavgaurav/CodeB_Internship_Project]

2 Week 5 & 6 Submission

[1]:
```
# Import Necessary Libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import train_test_split

import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc, confusion_matrix,␣
↪precision_recall_curve, average_precision_score
import seaborn as sns
import numpy as np
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.ensemble import RandomForestClassifier
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```
# import dataset

data_url = 'https://raw.githubusercontent.com/jadhavgaurav/
↪CodeB_Internship_Project/refs/heads/main/dataset_phishing.csv'

df = pd.read_csv(data_url)

df.sample(frac = 1)
```

[2]:

```
                                                     url  length_url  \
2901                             https://www.limerius.com/          25
4310   https://drive.google.com/file/d/1YV6DIzGh3i0YS…          84
10821                https://www.soundsnap.com/tags/modem          36
5654     http://agwa.cl/img/admin/invoice/adeb/adobe.php          47
464    https://drive.google.com/file/d/1_GGqmQXcOYjJZ…          70
…                                                    …         …
11281                      https://www.oikonomou-shop.gr/          30
9240   http://www.oracle.com/technetwork/database/ent…         100
7236   https://kwansasia.com/.%20/styles-link-done/d5…          80
4731   https://www.likealocalguide.com/freiburg/compa…          69
8904   http://blog.visme.co/passive-aggressive-behavi…          79

       length_hostname  ip  nb_dots  nb_hyphens  nb_at  nb_qm  nb_and  nb_or  \
2901                16   0        2           0      0      0       0      0
4310                16   0        2           0      0      1       0      0
10821               17   0        2           0      0      0       0      0
5654                 7   0        2           0      0      0       0      0
464                 16   0        2           1      0      0       0      0
…                  …  ..      …         …    …    …     …    …
11281               21   0        2           1      0      0       0      0
9240                14   0        3           3      0      0       0      0
7236                13   1        3           2      0      0       0      0
4731                23   0        2           3      0      0       0      0
8904                13   0        2           6      0      0       0      0

       …  domain_in_title  domain_with_copyright  whois_registered_domain  \
2901   …                1                      1                        0
4310   …                0                      0                        0
10821  …                0                      0                        0
5654   …                1                      0                        0
464    …                0                      1                        0
…     …              …                    …                      …
11281  …                0                      1                        1
9240   …                0                      0                        0
7236   …                1                      0                        0
4731   …                1                      1                        0
8904   …                0                      0                        0

       domain_registration_length  domain_age  web_traffic  dns_record  \
2901                          141        1320            0           0
4310                         2973        8348            1           0
10821                        1084        5125        18864           0
5654                           99          -1            0           0
464                          2974        8348            1           0
…                            …         …          …         …
11281                           0          -1       498528           0
```

```
9240                          132      11555       609         0
7236                          314         50         0         0
4731                          106       3546    201194         0
8904                          161       2394      4120         0

       google_index  page_rank      status
2901              0          2  legitimate
4310              1         10    phishing
10821             0          5  legitimate
5654              1          0    phishing
464               1         10    phishing
…               …        …         …
11281             0          2  legitimate
9240              1          7  legitimate
7236              1          0    phishing
4731              0          5  legitimate
8904              1          5  legitimate

[11430 rows x 89 columns]
```

3 Data Cleaning Report Phishing Website Detection

3.1 Dataset Overview

- **Total Records:** 11,430
- **Total Features (excluding target):** 87
- **Target Variable:** `status`
  - `0`: Legitimate
  - `1`: Phishing
- **Data Types:**
  - **Numerical (int64/float64):** 87
  - **Categorical/Object:** 1 (`url`)

3.1.1 Target Column

3.1.2 `status`

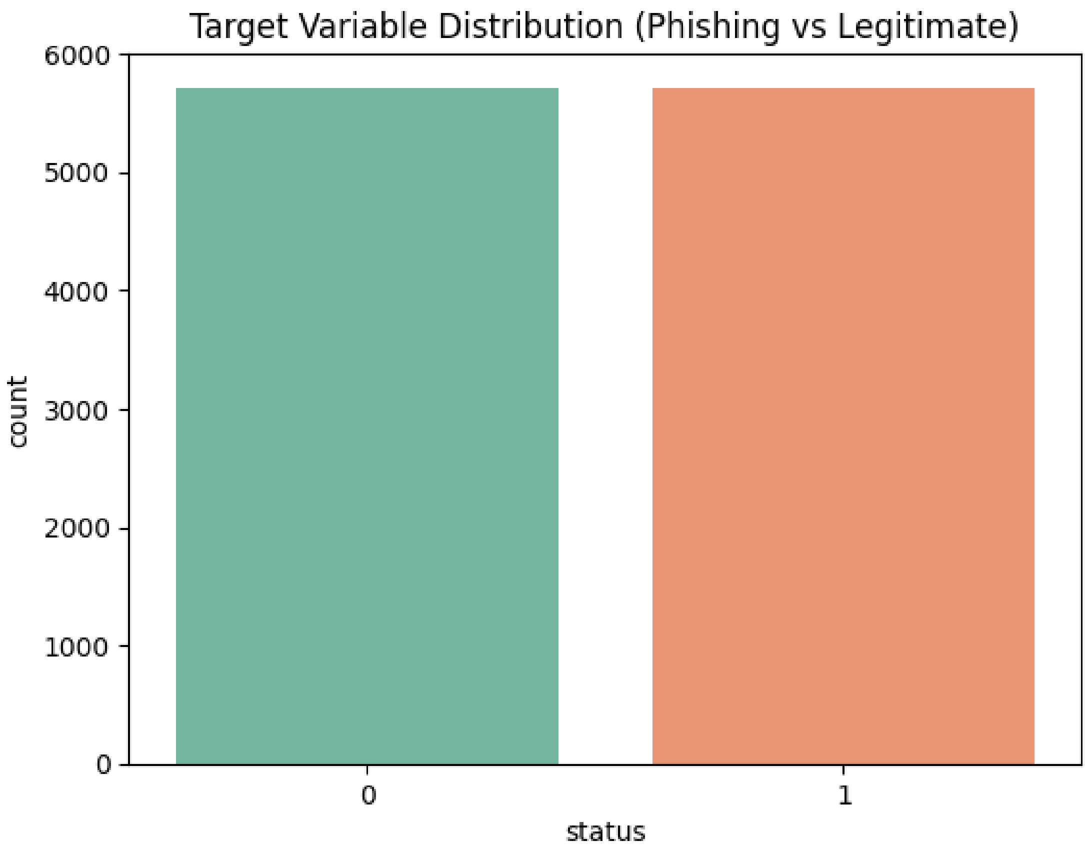
- **Description**: Binary label indicating if the website is phishing (`1`) or legitimate (`0`).
- **Relevance**: This is the variable to be predicted by the classification model.

---

[3]:
```
# Replace 'Legitimate' with 0 and 'Phishing' with 1 in the 'status' column
df['status'] = df['status'].map({'legitimate':0, 'phishing':1})

print(df['status'].value_counts())
```

```
status
0    5715
1    5715
Name: count, dtype: int64
```

[4]:
```
# Basic Info About Target Column and Visualize Target Distribution (Bar Plot)

# Check class distribution

sns.countplot(data=df, x='status', palette='Set2')
plt.title("Target Variable Distribution (Phishing vs Legitimate)")
plt.show()

print(df['status'].value_counts())
```




```
status
0    5715
1    5715
Name: count, dtype: int64
```

[5]:
```
numeric_features = df.select_dtypes(include=['int64', 'float64']).columns.
 ↪tolist()
categorical_features = df.select_dtypes(include='object').columns.tolist()

print("Numeric Features:", numeric_features)
print("Categorical Features:", categorical_features)
```

```
Numeric Features: ['length_url', 'length_hostname', 'ip', 'nb_dots',
'nb_hyphens', 'nb_at', 'nb_qm', 'nb_and', 'nb_or', 'nb_eq', 'nb_underscore',
'nb_tilde', 'nb_percent', 'nb_slash', 'nb_star', 'nb_colon', 'nb_comma',
'nb_semicolumn', 'nb_dollar', 'nb_space', 'nb_www', 'nb_com', 'nb_dslash',
'http_in_path', 'https_token', 'ratio_digits_url', 'ratio_digits_host',
'punycode', 'port', 'tld_in_path', 'tld_in_subdomain', 'abnormal_subdomain',
'nb_subdomains', 'prefix_suffix', 'random_domain', 'shortening_service',
'path_extension', 'nb_redirection', 'nb_external_redirection',
'length_words_raw', 'char_repeat', 'shortest_words_raw', 'shortest_word_host',
'shortest_word_path', 'longest_words_raw', 'longest_word_host',
'longest_word_path', 'avg_words_raw', 'avg_word_host', 'avg_word_path',
'phish_hints', 'domain_in_brand', 'brand_in_subdomain', 'brand_in_path',
'suspecious_tld', 'statistical_report', 'nb_hyperlinks', 'ratio_intHyperlinks',
'ratio_extHyperlinks', 'ratio_nullHyperlinks', 'nb_extCSS',
'ratio_intRedirection', 'ratio_extRedirection', 'ratio_intErrors',
'ratio_extErrors', 'login_form', 'external_favicon', 'links_in_tags',
'submit_email', 'ratio_intMedia', 'ratio_extMedia', 'sfh', 'iframe',
'popup_window', 'safe_anchor', 'onmouseover', 'right_clic', 'empty_title',
'domain_in_title', 'domain_with_copyright', 'whois_registered_domain',
'domain_registration_length', 'domain_age', 'web_traffic', 'dns_record',
'google_index', 'page_rank', 'status']
Categorical Features: ['url']
```

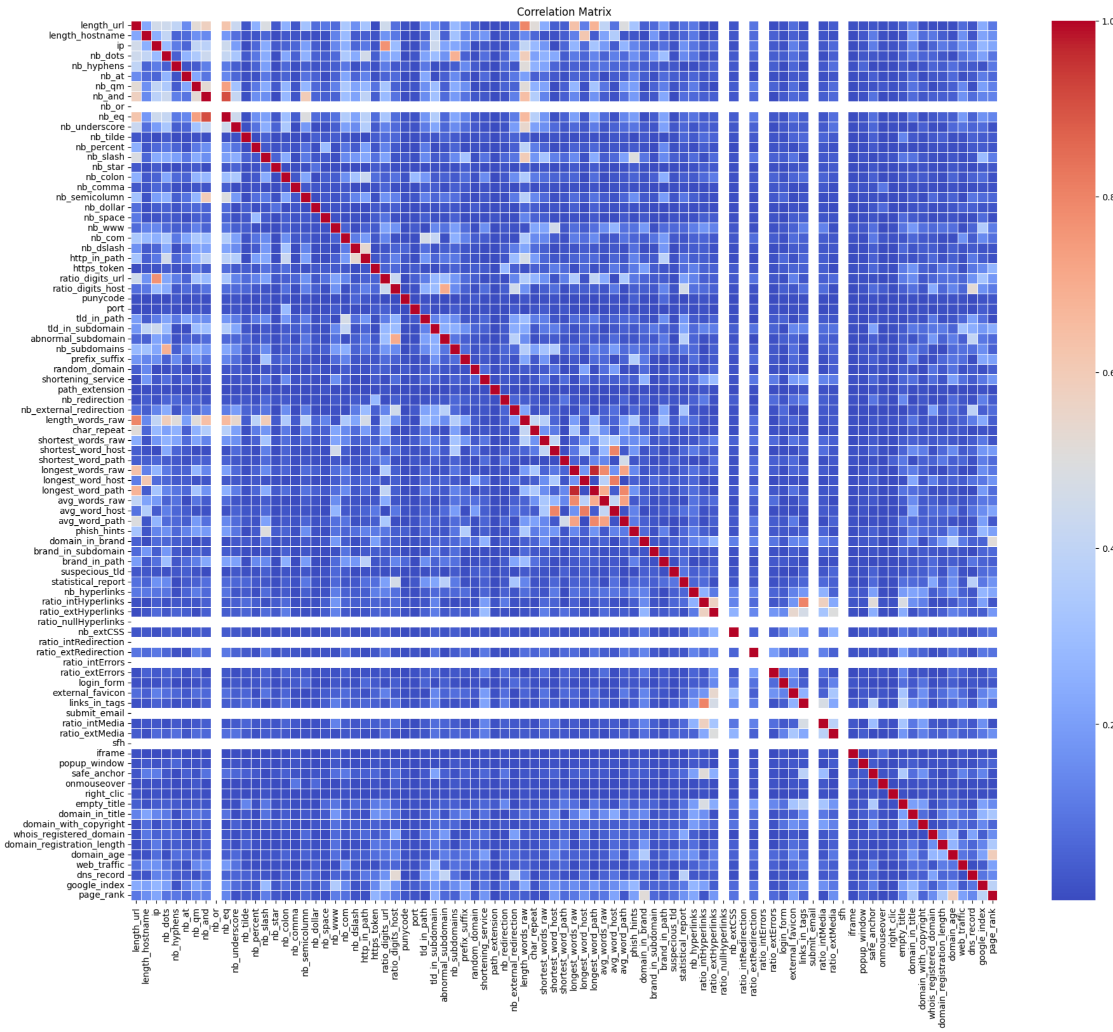
[6]:
```
# Dropping the 'url' column
# The 'url' column is not useful for training the machine learning model.

df.drop(columns=['url'], inplace=True)
```

4 Feature Selection Report

Step 1: Correlation Analysis

Remove features that are highly correlated with each other (e.g., correlation > 0.9 or < -0.9) to reduce multicollinearity.

[7]:
```
# Step 1: Compute correlation matrix
corr_matrix = df.drop('status', axis=1).corr().abs()  # Exclude target column
plt.figure(figsize=(22, 18))
sns.heatmap(corr_matrix, annot=False, cmap='coolwarm', linewidths=0.5)
plt.title("Correlation Matrix")
plt.show()
```



- The correlation heatmap was generated to visually inspect multicollinearity between features.
- Correlation threshold used: `0.90`

Heatmap legend:

`Red diagonal` = perfect correlation (with itself)

`Light blue` = weak or no correlation

`Orange/red`= strong correlation

[8]:
```
# Step 2: Select upper triangle of correlation matrix
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(bool))

# Step 3: Find features with correlation > 0.9
to_drop = [column for column in upper.columns if any(upper[column] > 0.9)]
print(f"Highly correlated features to drop (corr > 0.9):\n{to_drop}")
```

```
# Step 4: Drop the features from the dataset
df_reduced = df.drop(columns=to_drop)
print(f"\nShape before dropping: {df.shape}")
print(f"Shape after dropping: {df_reduced.shape}")
```

```
Highly correlated features to drop (corr > 0.9):
['nb_eq', 'longest_word_path']

Shape before dropping: (11430, 88)
Shape after dropping: (11430, 86)
```

- Computed the correlation matrix (Pearson correlation).
- Identified pairs of features with absolute correlation > 0.90.
- From each such pair, one feature was dropped to reduce redundancy.

Dropped Features:

- Based on correlation > 0.90, the following features were removed:

'nb_eq'

'longest_word_path'

- These features were highly correlated with other features carrying similar information.

[9]:
```
df_reduced.drop(columns=['avg_word_host'], inplace=True)  # Drop avg_word_host␣
↪column as per VIF analysis
```

4.0.1 2: Feature Selection using ANOVA F-test (f_classif)

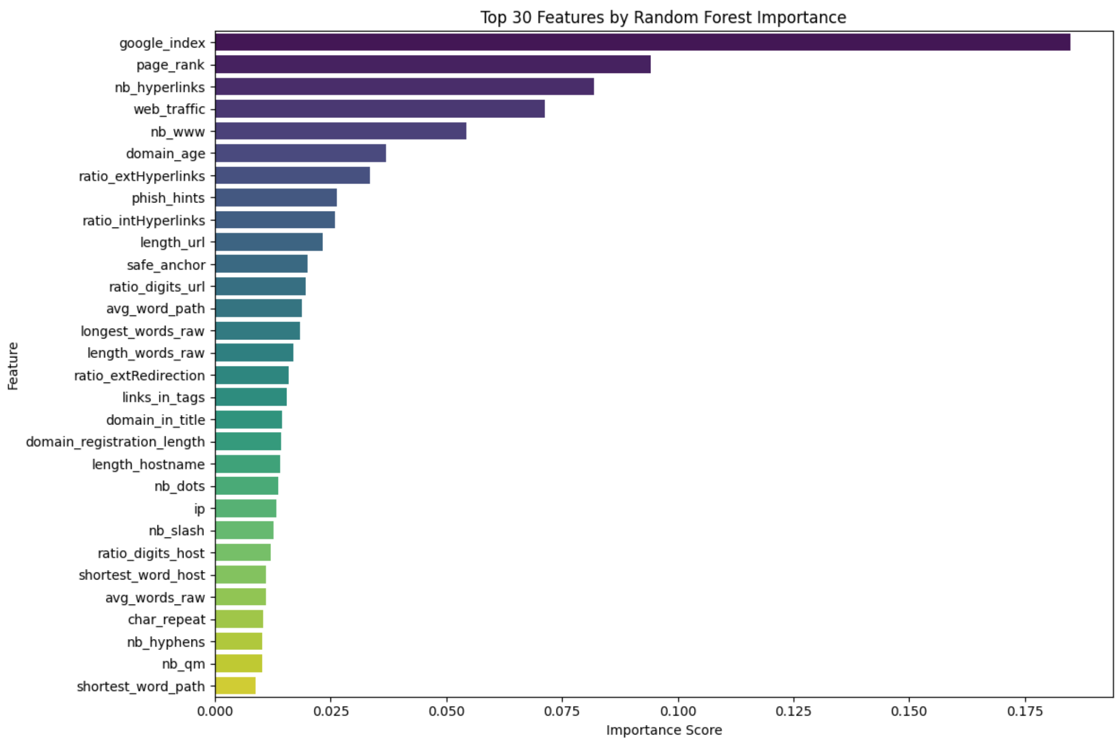
[10]:
```
from sklearn.feature_selection import SelectKBest, f_classif

X = df_reduced.drop(columns=['status'])
y = df_reduced['status']

# Apply ANOVA F-test
selector = SelectKBest(score_func=f_classif, k=30)  # Select top 20 features
X_kbest = selector.fit_transform(X, y)

# Get selected feature names
selected_features_f_classif = X.columns[selector.get_support()]
print("Top 30 Features selected using f_classif:")
print(selected_features_f_classif)
```

```
Top 30 Features selected using f_classif:
Index(['length_url', 'length_hostname', 'ip', 'nb_dots', 'nb_qm', 'nb_and',
       'nb_slash', 'nb_www', 'ratio_digits_url', 'ratio_digits_host',
       'tld_in_subdomain', 'prefix_suffix', 'length_words_raw',
       'shortest_word_host', 'longest_words_raw', 'avg_words_raw',
```

```
       'avg_word_path', 'phish_hints', 'nb_hyperlinks', 'ratio_intHyperlinks',
       'links_in_tags', 'ratio_intMedia', 'safe_anchor', 'empty_title',
       'domain_in_title', 'domain_with_copyright',
       'domain_registration_length', 'domain_age', 'google_index',
       'page_rank'],
      dtype='object')
```

4.0.2 3: Random Forest Feature Importance

[11]:
```python
# Load dataset (assuming df is already preprocessed and target is separated)
X = df_reduced.drop('status', axis=1)
y = df_reduced['status']

# Train Random Forest
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X, y)

# Get feature importances
importances = pd.Series(rf.feature_importances_, index=X.columns)
top_30_features = importances.sort_values(ascending=False).head(30)

# Plot
plt.figure(figsize=(12, 8))
sns.barplot(x=top_30_features.values, y=top_30_features.index,
 ↪palette='viridis')
plt.title('Top 30 Features by Random Forest Importance')
plt.xlabel('Importance Score')
plt.ylabel('Feature')
plt.tight_layout()
plt.show()
```



4.0.3 4: Apply RFE (Recursive Feature Elimination)

[12]:
```python
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import RFE

# Use top 40 features for RFE
X_top30 = X[top_30_features.index]

# Apply RFE with Logistic Regression
lr = LogisticRegression(solver='liblinear', random_state=42)
rfe = RFE(estimator=lr, n_features_to_select=20)
rfe.fit(X_top30, y)

# Get selected feature names
selected_features_rfe = X_top30.columns[rfe.support_]
print("Top 20 features selected by RFE:\n")
print(selected_features_rfe)
```

```
Top 20 features selected by RFE:

Index(['google_index', 'page_rank', 'nb_www', 'ratio_extHyperlinks',
       'phish_hints', 'ratio_intHyperlinks', 'ratio_digits_url',
       'avg_word_path', 'longest_words_raw', 'length_words_raw',
       'ratio_extRedirection', 'domain_in_title', 'nb_dots', 'ip',
```

```
 'ratio_digits_host', 'shortest_word_host', 'avg_words_raw',
 'nb_hyphens', 'nb_qm', 'shortest_word_path'],
dtype='object')
```

4.0.4 Final Selected Features from

`selected_features_rfe` → top 20 features from RFE on top 30 RF features

`selected_features_f_classif` → top 30 features from f_classif

[13]:
```
# Convert both to sets
rfe_features_set = set(selected_features_rfe)
f_classif_features_set = set(selected_features_f_classif)

# Take intersection
final_selected_features = list(rfe_features_set.union(f_classif_features_set))

print("Final Selected Features (Intersection of RFE and f_classif):")
print(final_selected_features)
print(f"Number of final selected features: {len(final_selected_features)}")
```

```
Final Selected Features (Intersection of RFE and f_classif):
['nb_hyphens', 'nb_dots', 'empty_title', 'length_hostname', 'longest_words_raw',
'domain_in_title', 'ratio_intMedia', 'links_in_tags', 'ratio_intHyperlinks',
'prefix_suffix', 'length_words_raw', 'safe_anchor', 'shortest_word_path',
'nb_www', 'avg_words_raw', 'nb_and', 'nb_slash', 'domain_registration_length',
'domain_age', 'ip', 'nb_qm', 'shortest_word_host', 'page_rank',
'ratio_extRedirection', 'length_url', 'phish_hints', 'ratio_digits_url',
'ratio_extHyperlinks', 'nb_hyperlinks', 'avg_word_path', 'ratio_digits_host',
'tld_in_subdomain', 'domain_with_copyright', 'google_index']
Number of final selected features: 34
```

[14]:
```
# Subset the dataframe to final selected features
X_vif = df_reduced[final_selected_features]

# X_vif = X_vif.drop(columns=['avg_word_host'])

# Compute VIF
vif_data = pd.DataFrame()
vif_data["Feature"] = X_vif.columns
vif_data["VIF"] = [variance_inflation_factor(X_vif.values, i) for i in␣
↪range(X_vif.shape[1])]

# Sort VIF descending
vif_data = vif_data.sort_values(by="VIF", ascending=False)

print("VIF for Final Selected Features:")
print(vif_data)
```

```
VIF for Final Selected Features:
                      Feature        VIF
10            length_words_raw  26.646784
14               avg_words_raw  22.677655
24                  length_url  21.356093
8          ratio_intHyperlinks  17.695732
16                    nb_slash  16.004551
1                      nb_dots  11.074524
3              length_hostname  10.018208
4            longest_words_raw   8.455121
29               avg_word_path   8.351384
7                links_in_tags   7.433357
5              domain_in_title   5.553849
22                   page_rank   5.356246
21           shortest_word_host   4.893766
26             ratio_digits_url   4.508979
18                  domain_age   4.483027
27         ratio_extHyperlinks   4.213635
19                          ip   3.718532
33                google_index   3.634672
15                      nb_and   2.981160
6             ratio_intMedia   2.974564
0                   nb_hyphens   2.916684
12           shortest_word_path   2.902547
11                 safe_anchor   2.861841
13                      nb_www   2.772176
2                  empty_title   2.450279
20                       nb_qm   2.128720
32        domain_with_copyright   2.101064
31             tld_in_subdomain   1.972449
25                  phish_hints   1.833878
30           ratio_digits_host   1.726988
9                prefix_suffix   1.718168
17  domain_registration_length   1.603927
28                nb_hyperlinks   1.593017
23        ratio_extRedirection   1.540672
```

[15]:

```
features_to_drop_vif = [
    'length_words_raw',
    'avg_words_raw',
    'length_url',
    'ratio_intHyperlinks',
    'nb_slash',
    'nb_dots',
]
```

[16]:
```
# Final Set of Features After VIF Cleaning

final_features_vif = list(set(final_selected_features) -␣
 ↪set(features_to_drop_vif))
print(f"Number of final features after VIF cleaning: {len(final_features_vif)}")
print("Final Features After VIF Cleaning:")
final_features_vif
```

```
Number of final features after VIF cleaning: 28
Final Features After VIF Cleaning:
```

[16]:
```
['nb_hyphens',
 'empty_title',
 'length_hostname',
 'longest_words_raw',
 'ratio_intMedia',
 'domain_in_title',
 'links_in_tags',
 'prefix_suffix',
 'safe_anchor',
 'shortest_word_path',
 'nb_www',
 'nb_and',
 'domain_registration_length',
 'domain_age',
 'ip',
 'nb_qm',
 'shortest_word_host',
 'page_rank',
 'ratio_extRedirection',
 'phish_hints',
 'ratio_digits_url',
 'ratio_extHyperlinks',
 'nb_hyperlinks',
 'avg_word_path',
 'ratio_digits_host',
 'tld_in_subdomain',
 'domain_with_copyright',
 'google_index']
```

4.1 Applied Steps for Feature Selection Process:

4.1.1 1. Correlation Analysis

- Removed highly correlated features (`corr > 0.9`)
- **Dropped:** `'nb_eq'`, `'longest_word_path'`
- **Reduced from 88 to 86 features**

4.1.2 2. ANOVA (f_classif)

- Selected **top 30 features** based on **univariate F-test**
- Suitable for **numerical features** with **categorical target**

4.1.3 3. Random Forest Feature Importance

- Trained a **Random Forest Classifier**
- Retrieved **top 30 features** using `feature_importances_`

4.1.4 4. Recursive Feature Elimination (RFE)

- Applied **RFE** with Random Forest as estimator
- Selected another **top 30 important features**

4.1.5 5. Feature Union

- Took **intersection** of `f_classif_features_set` & `rfe_features_set`
- Created a **robust final feature set** using two strong methods

---

4.1.6 6. Variance Inflation Factor (VIF)

- Evaluated multicollinearity in final selected features

- Dropped 6 features with VIF > 10 to avoid redundancy

5 Feature Engineering

[17]:
```
# 1. URL Complexity Score
# Combines counts of common "suspicious" tokens into a single indicator.
# Phishing URLs often cram many special characters (www, -, ?, &) to obfuscate
 ↪their true destination.

df_reduced['url_complexity'] = (
      df_reduced['nb_www']
    + df_reduced['nb_hyphens']
    + df_reduced['nb_qm']
    + df_reduced['nb_and']
)
```

[18]:
```
# 2. Tag-to-Link Ratio
# Measures the density of "hidden" tags relative to visible hyperlinks.
# Fake pages load script/link tags disproportionately to real hyperlinks-high␣
↪ratios indicate suspicious embedding.

df_reduced['tag_to_link_ratio'] = df_reduced['links_in_tags'] /␣
↪(df_reduced['nb_hyperlinks'] + 1)
```

[19]:
```
# 3. Domain Numeric Intensity
# Scales the digit-density in the hostname by domain age (older domains with␣
↪many digits are rarer).
# Young domains with a high digit ratio are more likely auto-generated by␣
↪attackers; multiplying by domain_age highlights this risk.

df_reduced['domain_numeric_intensity'] = df_reduced['ratio_digits_host'] *␣
↪df_reduced['domain_age']
```

[20]:
```
# 4. Path Word Complexity
# Captures both the average word length and the longest word in the URL path.
# Extremely long or complex path segments often appear in phishing payload URLs-
this combines average and maximum word length in the path.

df_reduced['path_word_complexity'] = df_reduced['avg_word_path'] *␣
↪df_reduced['longest_words_raw']
```

[21]:
```
# Drop 5 low-importance/redundant features
features_to_drop = [
    'domain_with_copyright',
    'ratio_intMedia',
    'google_index',
    'page_rank',
    'safe_anchor'
]

# Drop from X_train and X_test
df_reduced = df_reduced.drop(columns=features_to_drop)

# Update the final_features_vif list
final_features_vif = [feature for feature in final_features_vif if feature not␣
↪in features_to_drop]

# Add the newly engineered features
new_engineered_features = ['url_complexity', 'tag_to_link_ratio',␣
↪'domain_numeric_intensity', 'path_word_complexity']
final_features_vif.extend(new_engineered_features)

#  Check final feature count
```

```
print("Total final features after update:", len(final_features_vif))
final_features_vif
```

```
Total final features after update: 27
```

```
[21]: ['nb_hyphens',
 'empty_title',
 'length_hostname',
 'longest_words_raw',
 'domain_in_title',
 'links_in_tags',
 'prefix_suffix',
 'shortest_word_path',
 'nb_www',
 'nb_and',
 'domain_registration_length',
 'domain_age',
 'ip',
 'nb_qm',
 'shortest_word_host',
 'ratio_extRedirection',
 'phish_hints',
 'ratio_digits_url',
 'ratio_extHyperlinks',
 'nb_hyperlinks',
 'avg_word_path',
 'ratio_digits_host',
 'tld_in_subdomain',
 'url_complexity',
 'tag_to_link_ratio',
 'domain_numeric_intensity',
 'path_word_complexity']
```

5.1 ## Feature Engineering and Feature Selection Report

5.1.1 Key Insights from Feature Selection Process

The feature selection pipeline combined statistical rigor and machine learning techniques to ensure an optimal set of predictive variables:

1. **Correlation Analysis**
   - Identified and removed highly correlated features (`corr > 0.9`) to reduce redundancy.
   - **Dropped:** `'nb_eq'`, `'longest_word_path'`
   - Reduced feature count from **88 to 86**.

2. **ANOVA F-Test (f_classif)**
   - Used to select the **top 30 features** based on **univariate analysis**.

- Suitable for identifying strong relationships between **numerical features** and the **categorical target**.

3. **Random Forest Feature Importance**
   - Leveraged `feature_importances_` from a **trained Random Forest** to extract **top 30 influential features**.
4. **Recursive Feature Elimination (RFE)**
   - Applied **RFE with Random Forest** as the estimator.
   - Selected another **top 30 features**, enhancing robustness.
5. **Feature Intersection (Union Strategy)**
   - Took the **intersection** of features selected by both **f_classif** and **RFE**.
   - Resulted in a **robust and refined feature set** based on two complementary methods.
6. **Variance Inflation Factor (VIF)**
   - Dropped **6 features** with **VIF $>$ 10** to mitigate multicollinearity issues:
     - `length_words_raw`, `avg_words_raw`, `length_url`, `ratio_intHyperlinks`, `nb_slash`, `nb_dots`

5.1.2 Engineered Features That Add High Predictive Value

The following features were engineered to capture phishing-specific patterns:

Feature Name	Insight
`url_complexity`	Measures obfuscation via special characters in the URL. High values are often seen in phishing.
`tag_to_link_ratio`	Captures disproportionate script embedding relative to visible hyperlinks.
`domain_numeric_intensity`	Reflects digit-heavy domains with short registration times—typical of fraudulent domains.
`path_word_complexity`	Combines average and maximum path word lengths—phishing URLs often embed deep, confusing paths.

5.1.3 Dropped Redundant / Low-Predictive Features (Post-VIF)

The following features were removed to reduce redundancy as they were used in new feature formations:

- domain_with_copyright
- ratio_intMedia
- google_index
- page_rank
- safe_anchor

Following features were dropped because of high VIF - length_words_raw - avg_words_raw - length_url - ratio_intHyperlinks - nb_slash - nb_dots

---

6 Split Dataset into Train and Test set

[22]:
```
from sklearn.model_selection import train_test_split

# Define final feature set and target
X_final = df_reduced[final_features_vif]
y_final = df_reduced['status']

# Perform stratified train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X_final, y_final,
    test_size=0.2,
    random_state=42,
    stratify=y_final  # maintain class distribution
)

# Generate report
train_size = X_train.shape[0]
test_size = X_test.shape[0]
total_size = len(y_final)

train_percent = round((train_size / total_size) * 100, 2)
test_percent = round((test_size / total_size) * 100, 2)

print("  Data Splitting Report:")
print(f"  Total records: {total_size}")
print(f"  Training set: {train_size} records ({train_percent}%)")
print(f"  Testing set: {test_size} records ({test_percent}%)")

print("\n  Target Distribution Check:")
print("Train set distribution:")
print(y_train.value_counts(normalize=True).map(lambda x: f"{x:.2%}"))

print("\nTest set distribution:")
print(y_test.value_counts(normalize=True).map(lambda x: f"{x:.2%}"))
```

```
 Data Splitting Report:
```

```
 Total records: 11430
 Training set: 9144 records (80.0%)
 Testing set: 2286 records (20.0%)

 Target Distribution Check:
Train set distribution:
status
0    50.00%
1    50.00%
Name: proportion, dtype: object

Test set distribution:
status
1    50.00%
0    50.00%
Name: proportion, dtype: object
```

6.1 Skewness Handling Report

Technique Applied

- **Transformer:** Yeo–Johnson PowerTransformer
- **Library:** `sklearn.preprocessing.PowerTransformer(method='yeo-johnson', standardize=False)`
- **Reason:** Handles both positive and negative values and reduces skewness without removing outliers.

---

[23]:
```
print("\nSkewness of Features:")
X_train.skew()
```

```
Skewness of Features:
```

[23]:
```
nb_hyphens                    4.034987
empty_title                   2.265138
length_hostname               4.522406
longest_words_raw            14.463195
domain_in_title              -1.328934
links_in_tags                -0.148617
prefix_suffix                 1.483091
shortest_word_path            4.649295
nb_www                        0.264874
nb_and                       10.090766
domain_registration_length   10.801880
domain_age                    0.168107
```

```
ip                             1.972296
nb_qm                          2.480994
shortest_word_host             2.296740
ratio_extRedirection           2.232868
phish_hints                    3.249916
ratio_digits_url               2.205006
ratio_extHyperlinks            1.018971
nb_hyperlinks                  7.816814
avg_word_path                 12.714639
ratio_digits_host              5.615369
tld_in_subdomain               4.147150
url_complexity                 4.126829
tag_to_link_ratio              5.024884
domain_numeric_intensity       5.877711
path_word_complexity          32.492235
dtype: float64
```

[24]:
```python
from sklearn.preprocessing import PowerTransformer

# Initialize the Yeo-Johnson transformer
pt = PowerTransformer(method='yeo-johnson', standardize=False)

# Fit the transformer on the training data and transform the training data
X_train_transformed = pt.fit_transform(X_train)

# Use the fitted transformer to transform the test data
X_test_transformed = pt.transform(X_test)

# Optional: Check skewness on transformed data
print("Skewness after Yeo-Johnson transform (Train):\n", pd.
 ↪DataFrame(X_train_transformed, columns=X_train.columns).skew().
 ↪sort_values(ascending=False))
print("Skewness after Yeo-Johnson transform (Test):\n", pd.
 ↪DataFrame(X_test_transformed, columns=X_test.columns).skew().
 ↪sort_values(ascending=False))
```

```
Skewness after Yeo-Johnson transform (Train):
 tld_in_subdomain               4.147150
nb_and                         3.512775
empty_title                    2.265138
ratio_digits_host              2.199596
nb_qm                          2.130345
ip                             1.972296
phish_hints                    1.701765
prefix_suffix                  1.483091
ratio_digits_url               0.720100
domain_numeric_intensity       0.656725
ratio_extRedirection           0.650762
```

```
nb_hyphens                    0.563168
tag_to_link_ratio             0.364356
ratio_extHyperlinks           0.319543
nb_www                        0.219986
url_complexity                0.070897
shortest_word_host            0.018237
shortest_word_path            0.005782
avg_word_path                -0.013200
path_word_complexity         -0.015818
length_hostname              -0.031823
nb_hyperlinks                -0.040903
domain_registration_length   -0.071173
longest_words_raw            -0.097140
links_in_tags                -0.491997
domain_age                   -0.765253
domain_in_title              -1.328934
dtype: float64
Skewness after Yeo-Johnson transform (Test):
 tld_in_subdomain              4.035637
nb_and                        3.346951
empty_title                   2.298328
ratio_digits_host             2.277310
nb_qm                         2.097703
ip                            1.886440
phish_hints                   1.594152
prefix_suffix                 1.474563
domain_numeric_intensity      0.676689
ratio_digits_url              0.643409
nb_hyphens                    0.635152
ratio_extRedirection          0.630630
tag_to_link_ratio             0.355226
ratio_extHyperlinks           0.295872
nb_www                        0.222480
length_hostname               0.205641
url_complexity                0.125121
avg_word_path                 0.053828
path_word_complexity          0.034095
longest_words_raw             0.014290
shortest_word_path            0.004271
shortest_word_host           -0.036910
nb_hyperlinks                -0.082770
domain_registration_length   -0.107386
links_in_tags                -0.507143
domain_age                   -0.760209
domain_in_title              -1.301086
dtype: float64
```

- After Yeo–Johnson transformation, **most features' skewness** is reduced **close to zero**, indicating more symmetric distributions.

- This makes subsequent **scaling** (RobustScaler) and **model training** more stable and effective.

7 Normalization/Scaling Report

7.1 Scaling : RobustScaler()

[25]:
```
from sklearn.preprocessing import RobustScaler

# 1. Store feature names before scaling
original_columns = X_train.columns

# 2. Scale the data
scaler = RobustScaler()
X_train_scaled = scaler.fit_transform(X_train_transformed)
X_test_scaled = scaler.transform(X_test_transformed)

# 3. Convert back to DataFrames with correct column names
X_train_scaled_df = pd.DataFrame(X_train_scaled, columns=original_columns)
X_test_scaled_df = pd.DataFrame(X_test_scaled, columns=original_columns)
```

[26]:
```
X_train_scaled_df.head(10)
```

[26]:
```
   nb_hyphens  empty_title  length_hostname  longest_words_raw  \
0    1.422259    -0.000000        -0.370679           0.153795
1    1.000000    -0.000000         1.892424           0.716696
2    1.255627    -0.000000        -1.211800           0.290551
3    1.255627    -0.000000        -0.370679           1.296221
4   -0.000000    -0.000000        -0.665448          -0.609188
5    1.000000     0.087006        -0.370679           0.413181
6    1.000000     0.087006         0.108688           1.540577
7    1.255627    -0.000000        -1.432313          -1.221937
8   -0.000000    -0.000000         0.211224          -0.886335
9   -0.000000    -0.000000        -0.512428          -0.609188

   domain_in_title  links_in_tags  prefix_suffix  shortest_word_path  nb_www  \
0         0.000000       0.215944         -0.000            0.000000     1.0
1         0.000000       0.215944          0.145            0.000000    -0.0
2       -10.750272      -0.784056         -0.000            0.000000     1.0
3       -10.750272      -0.784056         -0.000           -0.290007    -0.0
4         0.000000       0.150889         -0.000            0.202838    -0.0
5         0.000000      -0.784056          0.145            0.202838     1.0
6         0.000000       0.215944          0.145            0.000000    -0.0
7         0.000000      -0.784056         -0.000            0.202838    -0.0
8         0.000000      -0.784056         -0.000           -0.797162    -0.0
9       -10.750272      -0.461604         -0.000            0.202838     1.0
```

```
   nb_and  …  ratio_digits_url  ratio_extHyperlinks  nb_hyperlinks  \
0 -0.0000  …          1.167672            -0.254983       0.401851
1  0.0747  …          1.370121            -0.431575      -0.733252
2 -0.0000  …         -0.000000            -0.431575      -1.230173
3  0.0747  …          1.174977             0.866001       0.034638
4 -0.0000  …          1.319970            -0.221215       0.314936
5 -0.0000  …          1.431925            -0.431575      -1.230173
6 -0.0000  …          1.389039            -0.431575      -1.027061
7 -0.0000  …         -0.000000            -0.431575      -0.490133
8 -0.0000  …          1.394908             0.885031      -0.422995
9 -0.0000  …         -0.000000             0.767268      -0.107240

   avg_word_path  ratio_digits_host  tld_in_subdomain  url_complexity  \
0       0.185504          -0.000000         -0.000000        0.756403
1       0.213427          -0.000000          0.034415        0.652849
2       0.036928          -0.000000         -0.000000        0.515310
3      -0.078934          -0.000000         -0.000000        0.756403
4      -0.008166          -0.000000         -0.000000       -0.681264
5       0.204232          -0.000000         -0.000000        0.515310
6       0.265471          -0.000000         -0.000000        0.000000
7      -0.180524          -0.000000         -0.000000        0.318736
8      -0.840202           0.023677         -0.000000       -0.681264
9      -0.206308          -0.000000         -0.000000        0.000000

   tag_to_link_ratio  domain_numeric_intensity  path_word_complexity
0           0.296415                   -0.0000              0.138629
1           1.008329                   -0.0000              0.245673
2          -0.506928                   -0.0000              0.083297
3          -0.506928                   -0.0000              0.199656
4           0.314457                   -0.0000             -0.061817
5          -0.506928                   -0.0000              0.188726
6           1.066808                   -0.0000              0.450126
7          -0.506928                   -0.0000             -0.221424
8          -0.506928                    0.9186             -0.850800
9          -0.076988                   -0.0000             -0.170638

[10 rows x 27 columns]
```

7.2 Techniques Used:

- **Scaling Method Applied: RobustScaler**
- **Reason for Selection:**
  - **RobustScaler** was chosen because it is robust to outliers. Unlike **StandardScaler** or **MinMaxScaler**, it scales features using **median** and **IQR (Interquartile Range)**, making it suitable for datasets with outliers, which is common in real-world data.
  - It helps ensure that features are on a similar scale, which is important for machine

learning models like **SVM**, **Logistic Regression**, and **KNN**, which are sensitive to the scale of data.

7.3 Description of RobustScaler:

- **Scaler Formula:**

$$\text{scaled} = \frac{X - \text{median}(X)}{\text{IQR}(X)}$$

- **Median:** The middle value, less affected by outliers.
- **IQR:** The difference between the 75th and 25th percentiles, representing the range within which the central 50% of data points lie.
- **Impact of RobustScaler:**
  - **Prevents Outlier Influence:** The scaling technique is **not influenced by extreme values**.
  - **Preserves Distribution:** Data is centered and scaled based on the distribution within the interquartile range, making it **robust to skewed distributions**.

---

[27]:
```python
# Calculate original distribution (min, max)
original_stats = X_train.agg(['min', 'max']).T
original_stats.columns = ['Original Min', 'Original Max']


# X_train_scaled_df = pd.DataFrame(X_train_scaled, columns=X_train.columns)

# Calculate scaled distribution (min, max)
scaled_stats = X_train_scaled_df.agg(['min', 'max']).T
scaled_stats.columns = ['Scaled Min', 'Scaled Max']

# Combine both into a single table for comparison
comparison_df = pd.concat([original_stats, scaled_stats], axis=1)

# Print results
print("Before-and-After Feature Scaling (RobustScaler):\n")
print(comparison_df.round(3))
```

```
Before-and-After Feature Scaling (RobustScaler):

                          Original Min  Original Max  Scaled Min  Scaled Max
nb_hyphens                         0.0        32.000      -0.000       1.563
empty_title                        0.0         1.000      -0.000       0.087
length_hostname                    4.0       214.000      -3.638       4.130
longest_words_raw                  2.0       829.000      -3.997       3.338
```

domain_in_title	0.0	1.000	-10.750	0.000
links_in_tags	0.0	100.000	-0.784	0.216
prefix_suffix	0.0	1.000	-0.000	0.145
shortest_word_path	0.0	40.000	-0.797	1.758
nb_www	0.0	2.000	-0.000	1.342
nb_and	0.0	19.000	-0.000	0.075
domain_registration_length	-1.0	29829.000	-2.223	5.435
domain_age	-12.0	12874.000	-2.338	0.862
ip	0.0	1.000	-0.000	0.104
nb_qm	0.0	3.000	-0.000	0.096
shortest_word_host	1.0	39.000	-1.885	2.521
ratio_extRedirection	0.0	2.000	-0.000	1.465
phish_hints	0.0	10.000	-0.000	0.182
ratio_digits_url	0.0	0.724	-0.000	1.486
ratio_extHyperlinks	0.0	1.000	-0.432	0.885
nb_hyperlinks	0.0	4659.000	-1.230	2.729
avg_word_path	0.0	206.000	-0.840	2.999
ratio_digits_host	0.0	0.800	-0.000	0.024
tld_in_subdomain	0.0	1.000	-0.000	0.034
url_complexity	0.0	34.000	-0.681	1.447
tag_to_link_ratio	0.0	50.000	-0.507	1.067
domain_numeric_intensity	-0.8	3828.649	-1.659	0.927
path_word_complexity	0.0	83636.000	-0.851	2.596

7.3.1 Before-and-After Comparison of Numerical Feature Distributions:

7.3.2 Before Scaling:

- Features can have **different ranges** (e.g., one feature ranges from 0 to 10, while another ranges from 100 to 1000).
- Outliers could heavily influence the distributions (e.g., extremely large values may shift the mean).

7.3.3 After Scaling (RobustScaler):

- Features are scaled within a similar range but **without the influence of outliers**.
- The **central tendency** (median) and **spread** (IQR) are preserved and adjusted for each feature, so all features are on a comparable scale for model training.

All feature values are now on a similar scale centered around 0, making the model training more stable and faster.

[28]:
```python
# Final split dataset ready for model training
X_test_scaled_df.head(10)
```

[28]:
```
   nb_hyphens  empty_title  length_hostname  longest_words_raw  \
0    1.000000    -0.000000        -1.432313           0.153795
1    1.000000    -0.000000         1.389821           1.540577
2    1.000000    -0.000000         0.400177          -0.375356
```

3	-0.000000	0.087006	0.308213	0.801269
4	-0.000000	-0.000000	-0.370679	-0.375356
5	1.457444	-0.000000	0.108688	-0.174667
6	-0.000000	-0.000000	0.000000	-0.609188
7	-0.000000	0.087006	2.239898	0.624644
8	-0.000000	-0.000000	-0.370679	-0.174667
9	1.000000	-0.000000	0.570793	2.199471

	domain_in_title	links_in_tags	prefix_suffix	shortest_word_path	nb_www	\
0	0.000000	-0.784056	0.145	0.000000	-0.0	
1	0.000000	0.215944	0.145	0.590573	1.0	
2	0.000000	-0.784056	0.145	0.000000	-0.0	
3	0.000000	-0.784056	-0.000	0.681775	-0.0	
4	-10.750272	0.215944	-0.000	-0.797162	1.0	
5	-10.750272	-0.784056	0.145	0.202838	1.0	
6	0.000000	0.215944	-0.000	-0.797162	-0.0	
7	0.000000	-0.784056	-0.000	-0.797162	-0.0	
8	-10.750272	0.215944	-0.000	0.358520	-0.0	
9	-10.750272	0.215944	0.145	0.000000	1.0	

	nb_and	…	ratio_digits_url	ratio_extHyperlinks	nb_hyperlinks	\
0	-0.0	…	-0.000000	-0.431575	-1.230173	
1	-0.0	…	1.380355	-0.431575	0.339581	
2	-0.0	…	0.354286	0.845546	0.339581	
3	-0.0	…	-0.000000	-0.431575	-1.230173	
4	-0.0	…	-0.000000	-0.347178	0.134788	
5	-0.0	…	-0.000000	0.748947	0.736359	
6	-0.0	…	-0.000000	0.032664	-0.338941	
7	-0.0	…	0.842205	-0.431575	-1.230173	
8	-0.0	…	-0.000000	-0.301602	0.900572	
9	-0.0	…	1.461811	-0.431575	-0.528312	

	avg_word_path	ratio_digits_host	tld_in_subdomain	url_complexity	\
0	0.200523	-0.000000	-0.0	0.318736	
1	0.564626	-0.000000	-0.0	0.318736	
2	0.016058	-0.000000	-0.0	0.000000	
3	0.185504	-0.000000	-0.0	-0.681264	
4	-0.840202	-0.000000	-0.0	0.000000	
5	0.146611	-0.000000	-0.0	0.838215	
6	-0.840202	-0.000000	-0.0	-0.681264	
7	-0.840202	0.022058	-0.0	-0.681264	
8	0.210374	-0.000000	-0.0	-0.681264	
9	0.545388	-0.000000	-0.0	0.515310	

	tag_to_link_ratio	domain_numeric_intensity	path_word_complexity
0	-0.506928	-0.000000	0.146031
1	0.349175	-0.000000	0.598789

```
2           -0.506928                  -0.000000             -0.020404
3           -0.506928                  -0.000000              0.247026
4            0.522042                  -0.000000             -0.850800
5           -0.506928                  -0.000000              0.072134
6            0.852320                  -0.000000             -0.850800
7           -0.506928                   0.926473             -0.850800
8           -0.073119                  -0.000000              0.103214
9            0.940470                  -0.000000              0.804899

[10 rows x 27 columns]
```

8 Model Training

[29]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from xgboost import XGBClassifier

from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪f1_score, roc_auc_score, classification_report
import pandas as pd

# Initialize models
models = {
    "Logistic Regression": LogisticRegression(random_state=42),
    "Decision Tree": DecisionTreeClassifier(random_state=42),
    "Random Forest": RandomForestClassifier(random_state=42),
    "XGBoost": XGBClassifier(random_state=42, use_label_encoder=False,␣
 ↪eval_metric='logloss'),
    "SVM": SVC(probability=True, random_state=42),
    "KNN": KNeighborsClassifier()
}

# DataFrame to store results
results = []

# Train and evaluate each model
for name, model in models.items():
    model.fit(X_train_scaled_df, y_train)
    y_pred = model.predict(X_test_scaled_df)
    y_proba = model.predict_proba(X_test_scaled_df)[:, 1] if hasattr(model,␣
 ↪"predict_proba") else None

    results.append({
```

```
        "Model": name,
        "Accuracy": accuracy_score(y_test, y_pred),
        "Precision": precision_score(y_test, y_pred),
        "Recall": recall_score(y_test, y_pred),
        "F1-Score": f1_score(y_test, y_pred),
        "ROC-AUC": roc_auc_score(y_test, y_proba) if y_proba is not None else␣
 ↪"N/A"
    })

# Display results
results_df = pd.DataFrame(results).sort_values(by="F1-Score", ascending=False)
print("  Model Comparison:")
display(results_df)
```

```
  File "c:\Users\gaura\anaconda3\envs\phishing_env\lib\site-
packages\joblib\externals\loky\backend\context.py", line 257, in
_count_physical_cores
    cpu_info = subprocess.run(
  File "c:\Users\gaura\anaconda3\envs\phishing_env\lib\subprocess.py", line 503,
in run
    with Popen(*popenargs, **kwargs) as process:
  File "c:\Users\gaura\anaconda3\envs\phishing_env\lib\subprocess.py", line 971,
in __init__
    self._execute_child(args, executable, preexec_fn, close_fds,
  File "c:\Users\gaura\anaconda3\envs\phishing_env\lib\subprocess.py", line
1456, in _execute_child
    hp, ht, pid, tid = _winapi.CreateProcess(executable, args,
```

```
 Model Comparison:
```

	Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
2	Random Forest	0.948381	0.942956	0.954506	0.948696	0.986541
3	XGBoost	0.947944	0.941379	0.955381	0.948328	0.983886
5	KNN	0.909886	0.908457	0.911636	0.910044	0.957889
4	SVM	0.899825	0.889267	0.913386	0.901165	0.958717
1	Decision Tree	0.896763	0.887938	0.908136	0.897924	0.896763
0	Logistic Regression	0.887577	0.885217	0.890639	0.887920	0.949259

8.0.1 Best Performing Model: Random Forest Classifier

Insights & Justification - Highest Recall (0.956): Effectively identifies phishing websites with minimal false negatives.

- Best ROC-AUC Score (0.986): Demonstrates excellent ability to distinguish between classes.
- Strong F1-Score: Balanced precision and recall, indicating overall robustness.

Random Forest (Best Performer): - Achieved highest overall performance on all key metrics.

- Particularly strong recall (0.9510), which is critical for phishing detection (catching as many phishing sites as possible).

- Robust to overfitting thanks to ensembling.
- Final model selected for deployment.

XGBoost: - Almost tied with Random Forest in F1-score and ROC-AUC.

- Slightly more complex but offers good interpretability with tools like SHAP.
- Suitable for production environments.

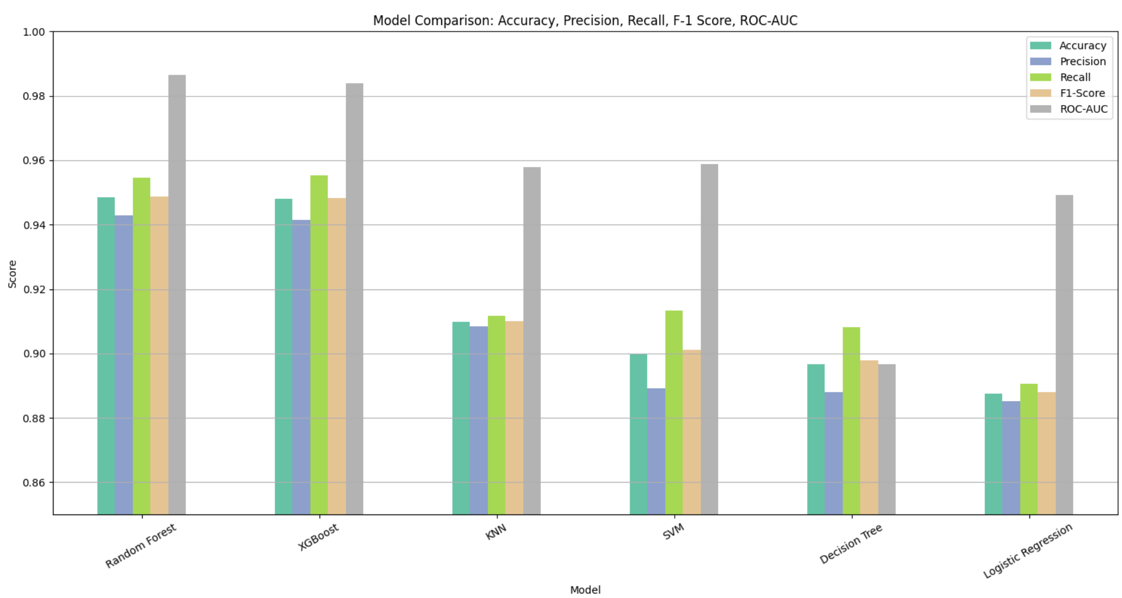
KNN & SVM: - Performed decently with ~0.91 F1-score.

- KNN is computationally expensive at scale and not ideal for real-time systems.
- SVM is powerful but harder to tune and scale with large datasets.

Logistic Regression & Decision Tree: Baseline models.

- Logistic Regression is interpretable but underperformed on non-linear relationships.
- Decision Tree showed slightly better recall but prone to overfitting.

[30]:
```
# Plotting the results

results_df.set_index('Model').plot(kind='bar', figsize=(15, 8), colormap='Set2')
plt.title('Model Comparison: Accuracy, Precision, Recall, F-1 Score, ROC-AUC')
plt.ylabel('Score')
plt.ylim(0.85, 1.0)
plt.grid(axis='y')
plt.xticks(rotation=30)
plt.legend(loc='upper right')
plt.tight_layout()
plt.show()
```



9 Perform Hyperparameter Tuning for Random Forest Classifier

[31]:
```
# Step 1: Import and Set Up the Grid

from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

# Define the base model
rf = RandomForestClassifier(random_state=42)

# Hyperparameter grid
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'bootstrap': [True, False]
}
```

[32]:
```
# Step 2: Apply GridSearchCV

# Grid search with 5-fold cross-validation
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid,
                           cv=5, n_jobs=-1, verbose=2, scoring='roc_auc')

# Fit on training data
grid_search.fit(X_train_scaled_df, y_train)
```

```
Fitting 5 folds for each of 216 candidates, totalling 1080 fits
```

[32]:
```
GridSearchCV(cv=5, estimator=RandomForestClassifier(random_state=42), n_jobs=-1,
             param_grid={'bootstrap': [True, False],
                         'max_depth': [None, 10, 20, 30],
                         'min_samples_leaf': [1, 2, 4],
                         'min_samples_split': [2, 5, 10],
                         'n_estimators': [100, 200, 300]},
             scoring='roc_auc', verbose=2)
```

[33]:
```
# Step 3: Extract Best Parameters and Model

best_rf = grid_search.best_estimator_
print("Best Parameters:\n", grid_search.best_params_)
```

```
Best Parameters:
 {'bootstrap': False, 'max_depth': 20, 'min_samples_leaf': 1,
'min_samples_split': 2, 'n_estimators': 300}
```

9.0.1 Save the Best Random Forest Model with best hyperparameters

[41]:
```
import joblib
joblib.dump(best_rf, 'best_random_forest_model.pkl')
```

[41]:
```
['best_random_forest_model.pkl']
```

[34]:
```
# Step 4: Evaluate Tuned Model on Test Set



# Predict on test set
y_pred = best_rf.predict(X_test_scaled_df)
y_prob = best_rf.predict_proba(X_test_scaled_df)[:, 1]

# Evaluation
print("Classification Report:\n", classification_report(y_test, y_pred))
print("ROC-AUC Score:", roc_auc_score(y_test, y_prob))
```

```
Classification Report:
               precision    recall  f1-score   support

           0       0.96      0.94      0.95      1143
           1       0.94      0.96      0.95      1143

    accuracy                           0.95      2286
   macro avg       0.95      0.95      0.95      2286
weighted avg       0.95      0.95      0.95      2286

ROC-AUC Score: 0.9872869128454307
```

9.1 Trained Machine Learning Model & Hyperparameter Tuning Report

9.1.1 Model Used

- **Random Forest Classifier**
- Trained multiple machine learning models and chosen RandomForestClassifier for its robustness, ensemble learning capability, and high performance in binary classification.
- Highest Recall (0.956): Effectively identifies phishing websites with minimal false negatives.

9.1.2 Hyperparameter Tuning

- **Technique:** `GridSearchCV`
- **Cross-Validation:** 5-fold
- **Scoring Metric:** ROC-AUC

Parameter Grid:

```
param_grid = {
    'bootstrap': False,
    'max_depth': 20,
    'min_samples_leaf': 1,
    'min_samples_split': 2,
    'n_estimators': 300
    'bootstrap': [True, False]
}
```

Best Model Configuration (best_estimator_)

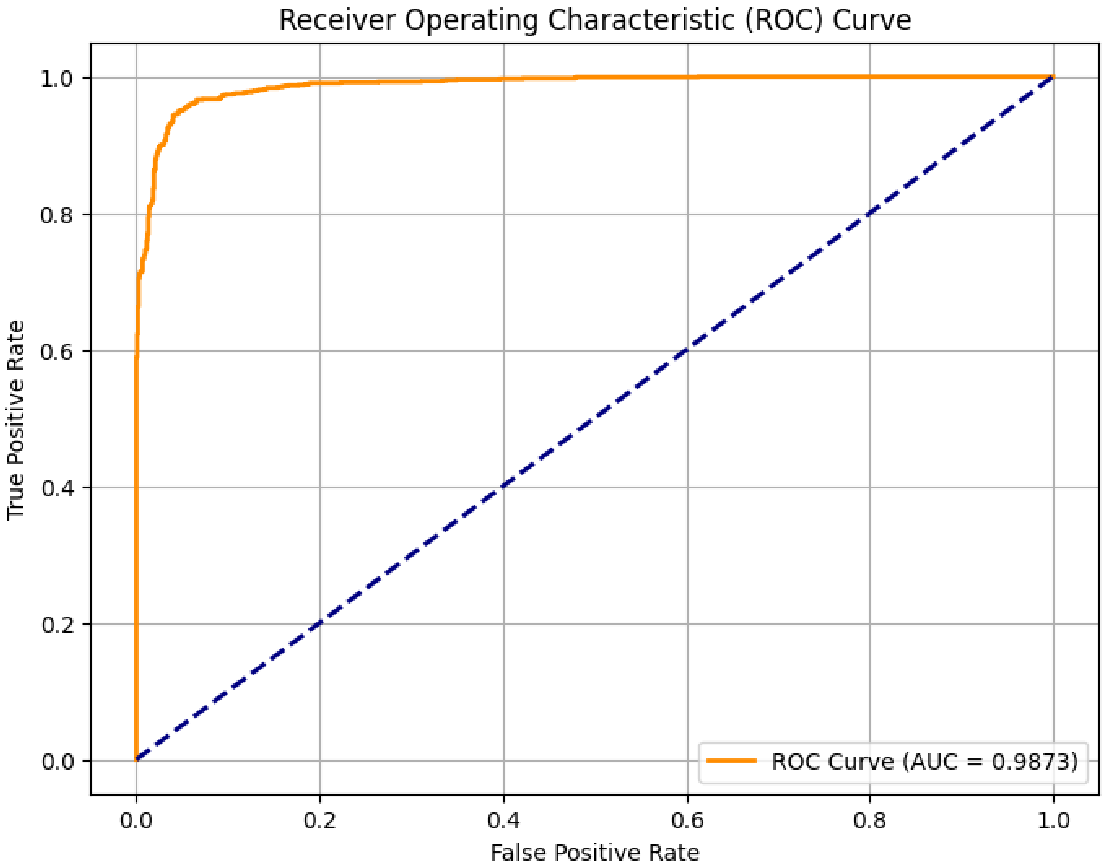
```
RandomForestClassifier(
    bootstrap=False,
    max_depth=30,
    min_samples_split=5,
    min_samples_leaf=1,
    n_estimators=300,
    random_state=42
)
```

- Best parameters were selected based on highest average ROC-AUC across cross-validation folds.
- The final model was used for evaluation, SHAP/LIME explainability, and deployment pipeline.
- It achieved high performance, making it a reliable model for phishing detection.

9.1.3 Plot the Evaluation Metrics

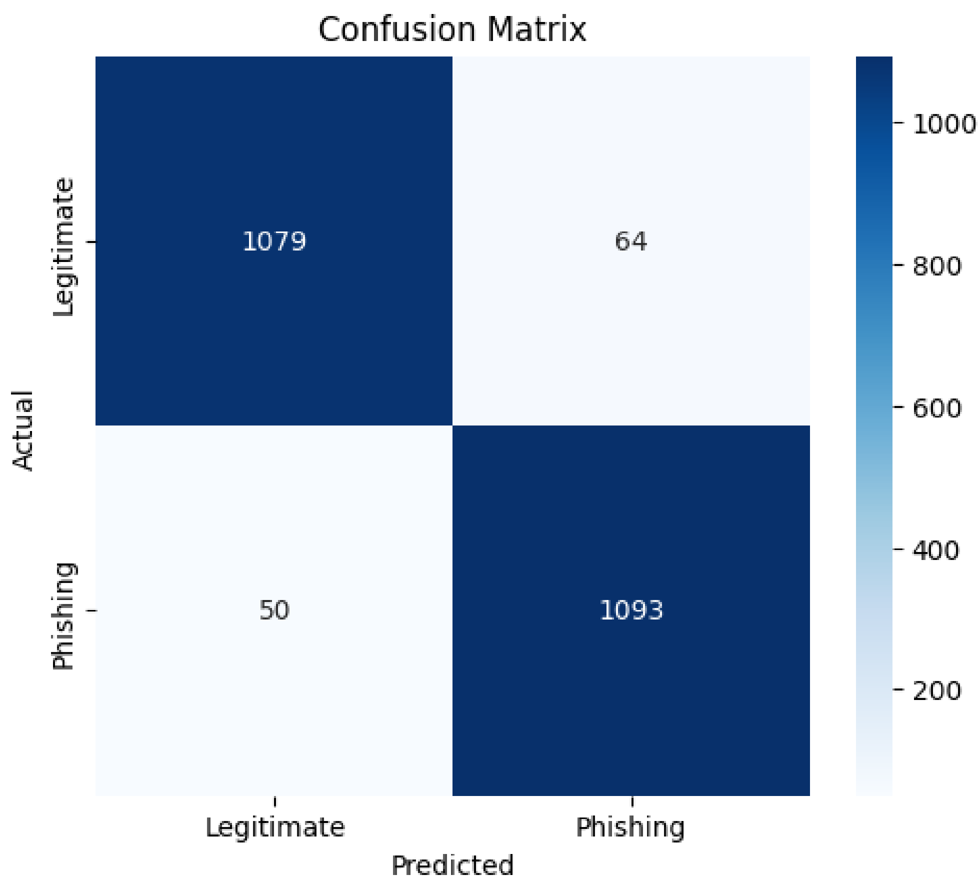
ROC Curve Plot

[35]:
```
# Predict probabilities for ROC
y_probs = best_rf.predict_proba(X_test_scaled_df)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_probs)
roc_auc = auc(fpr, tpr)

# Plot ROC Curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC Curve (AUC = {roc_auc:.
  ↪4f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.grid(True)
plt.show()
```



Confusion Matrix Heatmap

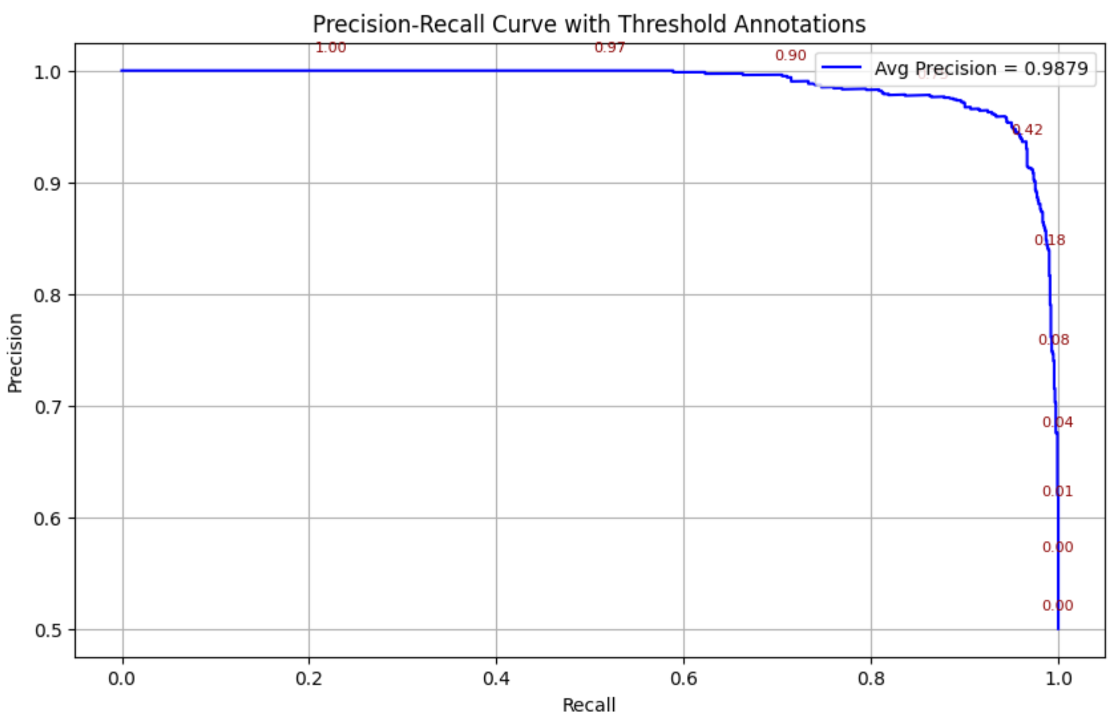
[36]:
```
# Predict labels
y_pred = best_rf.predict(X_test_scaled_df)

# Compute confusion matrix
cm = confusion_matrix(y_test, y_pred)
labels = ['Legitimate', 'Phishing']

# Plot heatmap
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=labels, yticklabels=labels)
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



Plot Precision-Recall Curve

[37]:
```
# Get predicted probabilities
y_probs = best_rf.predict_proba(X_test_scaled_df)[:, 1]

# Compute precision-recall pairs
precision, recall, thresholds = precision_recall_curve(y_test, y_probs)
avg_precision = average_precision_score(y_test, y_probs)

# Plot Precision-Recall curve
plt.figure(figsize=(10, 6))
plt.plot(recall, precision, label=f'Avg Precision = {avg_precision:.4f}',␣
  ↪color='blue')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve with Threshold Annotations')
plt.grid(True)

# Annotate some thresholds
```

```
for i in range(0, len(thresholds), max(1, len(thresholds) // 10)):
    plt.annotate(f"{thresholds[i]:.2f}",
                 (recall[i], precision[i]),
                 textcoords="offset points",
                 xytext=(0, 10),
                 ha='center',
                 fontsize=8,
                 color='darkred')

plt.legend(loc='upper right')
plt.show()
```



10 LIME Explainer for Random Forest Classifier

Step 1: Import and Create the LIME Explainer

[38]:
```
import lime
import lime.lime_tabular

# Create the LIME explainer
explainer = lime.lime_tabular.LimeTabularExplainer(
    training_data=np.array(X_train_scaled),
    feature_names=X_train.columns.tolist(),
```

```
    class_names=['Legitimate', 'Phishing'],
    mode='classification',
    verbose=True,
    feature_selection='auto'
)
```

Step 2: Explain Multiple Instances

[42]:
```
# Loop through multiple instances for explanation
for i in range(10):
    print(f"\n LIME Explanation for Instance {i} (True Label: {y_test.
 ↪iloc[i]})")

    exp = explainer.explain_instance(
        data_row=X_test_scaled[i],
        predict_fn=best_rf.predict_proba,
        num_features=len(X_test.columns)  # Explain all features
    )

    # Display in notebook (visual)
    exp.show_in_notebook(show_table=True)

    # Optional: Save to HTML
    exp.save_to_file(f'lime_explanation_instance_{i}.html')
```

```
 LIME Explanation for Instance 0 (True Label: 1)
Intercept 0.503550905072144
Prediction_local [0.85911573]
Right: 0.9487689393939394

<IPython.core.display.HTML object>


 LIME Explanation for Instance 1 (True Label: 1)
Intercept 0.7275414770150952
Prediction_local [0.59028459]
Right: 1.0

<IPython.core.display.HTML object>


 LIME Explanation for Instance 2 (True Label: 1)
Intercept 0.7170501558129858
Prediction_local [0.58807355]
Right: 0.9997701149425287

<IPython.core.display.HTML object>


 LIME Explanation for Instance 3 (True Label: 1)
```

```
Intercept 0.6543922972174165
Prediction_local [0.77503454]
Right: 0.9507096718813138
```

<IPython.core.display.HTML object>

```
 LIME Explanation for Instance 4 (True Label: 0)
Intercept 0.8729099116088367
Prediction_local [0.31851062]
Right: 0.01682567566256812
```

<IPython.core.display.HTML object>

```
 LIME Explanation for Instance 5 (True Label: 0)
Intercept 0.975932753105341
Prediction_local [0.11853016]
Right: 0.04709245540321392
```

<IPython.core.display.HTML object>

```
 LIME Explanation for Instance 6 (True Label: 0)
Intercept 0.8201018416826715
Prediction_local [0.41277829]
Right: 0.005240987083092346
```

<IPython.core.display.HTML object>

```
 LIME Explanation for Instance 7 (True Label: 1)
Intercept 0.6648568451717694
Prediction_local [0.60522493]
Right: 0.9857829836829837
```

<IPython.core.display.HTML object>

```
 LIME Explanation for Instance 8 (True Label: 0)
Intercept 0.9044102650536469
Prediction_local [0.11076633]
Right: 0.0
```

<IPython.core.display.HTML object>

```
 LIME Explanation for Instance 9 (True Label: 1)
Intercept 0.4792119133270608
Prediction_local [1.00375323]
Right: 0.98
```

<IPython.core.display.HTML object>

10.0.1 LIME Explanation Report (Instance-Level Model Interpretability)

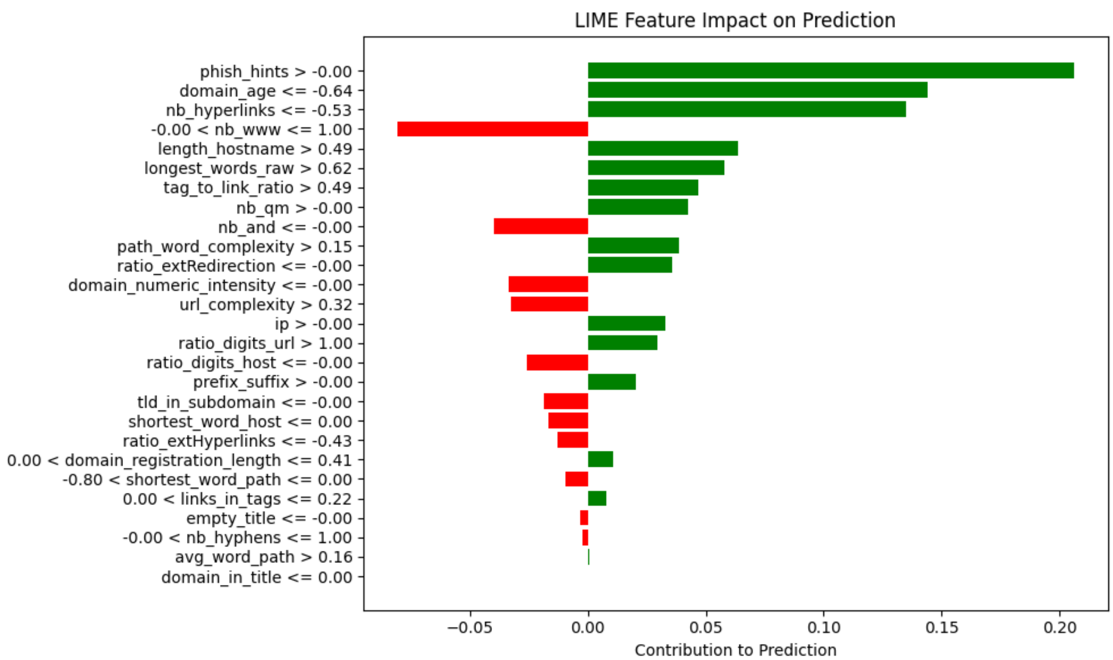
- LIME was applied on multiple test instances to interpret the Random Forest classifier predictions for phishing detection.
- Key features influencing predictions included:

`url_complexity`, `phish_hints`, `nb_www`, `nb_qm`, and `domain_numeric_intensity`

- Engineered features demonstrated strong explanatory power across all instances, validating their inclusion.
- LIME revealed that the same feature (e.g., prefix_suffix, ratio_digits_url) may have positive or negative impact depending on the context.
- Visualizations confirmed that most predictions were driven by a small subset of high-impact features, enhancing transparency and trust in the model.

Step 3: Plot Feature Weights as Bar Plot

[40]:
```python
# Plot feature impact bar chart (manual)
def plot_lime_weights(exp):
    weights = dict(exp.as_list())
    features = list(weights.keys())
    values = list(weights.values())

    plt.figure(figsize=(10, 6))
    plt.barh(features, values, color=['green' if v > 0 else 'red' for v in␣
 ↪values])
    plt.title("LIME Feature Impact on Prediction")
    plt.xlabel("Contribution to Prediction")
    plt.gca().invert_yaxis()
    plt.tight_layout()
    plt.show()

# Example: Plot for instance 0
plot_lime_weights(exp)
```



10.1 LIME Feature Impact - Phishing Detection

10.1.1 Features Positively Contributing to "Not Phishing"

These features indicate the URL is **likely safe**: - **`phish_hints > 0.00`** → Absence of phishing-related hints supports legitimacy. - **`domain_age > -0.64`** → Older domains are usually trustworthy. - **`nb_hyperlinks <= -0.53`** → Fewer hyperlinks suggest a safe page. - **`-0.00 < nb_www <= 1.00`** → Moderate use of "www" correlates with legitimate URLs. - **`length_hostname > 0.49`** → Longer hostnames are often used by real sites. - **`longest_words_raw > 0.62`** → Longer words in content support legitimacy. - **`tag_to_link_ratio > 0.49`** → Proper HTML structure suggests trustworthiness. - **`url_complexity > 0.32`** → Sophisticated URLs (not overly simple) tend to be legitimate. - **`ip > -0.00`** → Presence of a valid IP can be a positive sign. - **`ratio_digits_url > 1.00`** → Balanced use of digits is common in real sites. - **`path_word_complexity > 0.15`** → Complex paths often indicate dynamic, real content.

10.1.2 Features Negatively Impacting Prediction (Pointing to "Phishing")

These features raise suspicion: - **`nb_www in range -0.00 < nb_www <= 1.00`** (in excess) → May indicate phishing. - **`domain_numeric_intensity <= -0.00`** → Excessive numbers in the domain = red flag. - **`nb_qm > -0.00`** → Use of query parameters may imply phishing. - **`prefix_suffix > 0.00`** → Hyphenated domains often impersonate real brands. - **`tld_in_subdomain <= -0.00`** → Misuse of top-level domains in subdomains is suspicious. - **`domain_registration_length < 0.41`** → Recently registered domains are often phishing sites. - **`shortest_word_host <= 0.00`** → Very short words in host part may be autogenerated.
