4. MODEL TRAINING

January 2, 2026

Importing Libraries

[2]:
```
import pandas as pd
import numpy as np

from sklearn.model_selection import train_test_split, StratifiedKFold

from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier

from hyperopt import hp, tpe, STATUS_OK, Trials, fmin

from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, precision_recall_curve, ConfusionMatrixDisplay

import matplotlib.pyplot as plt
import shap

import pickle

import warnings
warnings.filterwarnings('ignore')
```

Reading the data

[3]:
```
df = pd.read_csv('data/processed/processed_data.csv')

df.head()
```

[3]:
```
   has_https  url_len  domain_len  path_len  query_len  url_depth  \
0          1       25          10         6          0          1
1          1       37          22         6          0          1
2          1       32          18         5          0          1
3          1       46          14         0         22          1
4          1       32          18         5          0          1

   subdomain_count  tld_len  url_has_ipv4  url_has_port  …  spl_char_count  \
0                1        2             0             0  …               5
```

```
1                  1          3               0               0  ...                   5
2                  1          3               0               0  ...                   6
3                  1          3               0               0  ...                   7
4                  1          3               0               0  ...                   6

   url_entropy  domain_entropy  sld_entropy  path_entropy  domain_token_count  \
0     3.863465        2.721928     2.235926      2.521641                   2
1     4.208925        3.629220     3.419382      2.521641                   2
2     4.452820        3.947703     3.000000      2.584963                   3
3     4.760096        3.664498     3.121928     -0.000000                   2
4     4.241729        3.836592     3.000000      2.584963                   3

   path_token_count  total_tokens  avg_token_length  class
0                 1             3              5.00      1
1                 1             3              9.00      1
2                 1             4              5.25      1
3                 1             3              8.50      1
4                 1             4              5.25      1

[5 rows x 30 columns]
```

Splitting the data

[4]:
```
X = df.drop(columns=['class']).values
y = df['class'].values
```

[5]:
```
X_train,X_test,y_train,y_test = train_test_split(X,y,train_size=0.
↪75,random_state=6)
```

Training the Models

[6]:
```
# Function to evaluate the models
def evaluate_model(y_true,y_pred):
    accuracy = accuracy_score(y_true,y_pred)
    precision = precision_score(y_true,y_pred)
    recall = recall_score(y_true,y_pred)
    f1 = f1_score(y_true,y_pred)

    print(f'Accuracy: {accuracy}')
    print(f'Precision: {precision}')
    print(f'Recall: {recall}')
    print(f'F1-Score: {f1}')
```

Random Forest Classifier

[7]:
```
rf_model = RandomForestClassifier()
rf_model.fit(X_train,y_train)

rf_pred_train = rf_model.predict(X_train)
```

```python
rf_pred_test = rf_model.predict(X_test)

print('Metrics of Random Forest on Training data:')
evaluate_model(y_train,rf_pred_train)

print()

print('Metrics of Random Forest on Testing data:')
evaluate_model(y_test,rf_pred_test)
```

```
Metrics of Random Forest on Training data:
Accuracy: 0.9980076354092102
Precision: 0.99923558711841
Recall: 0.9966551071103569
F1-Score: 0.997943678967653

Metrics of Random Forest on Testing data:
Accuracy: 0.9792412312097352
Precision: 0.9878127247265432
Recall: 0.9688903738352452
F1-Score: 0.9782600547246898
```

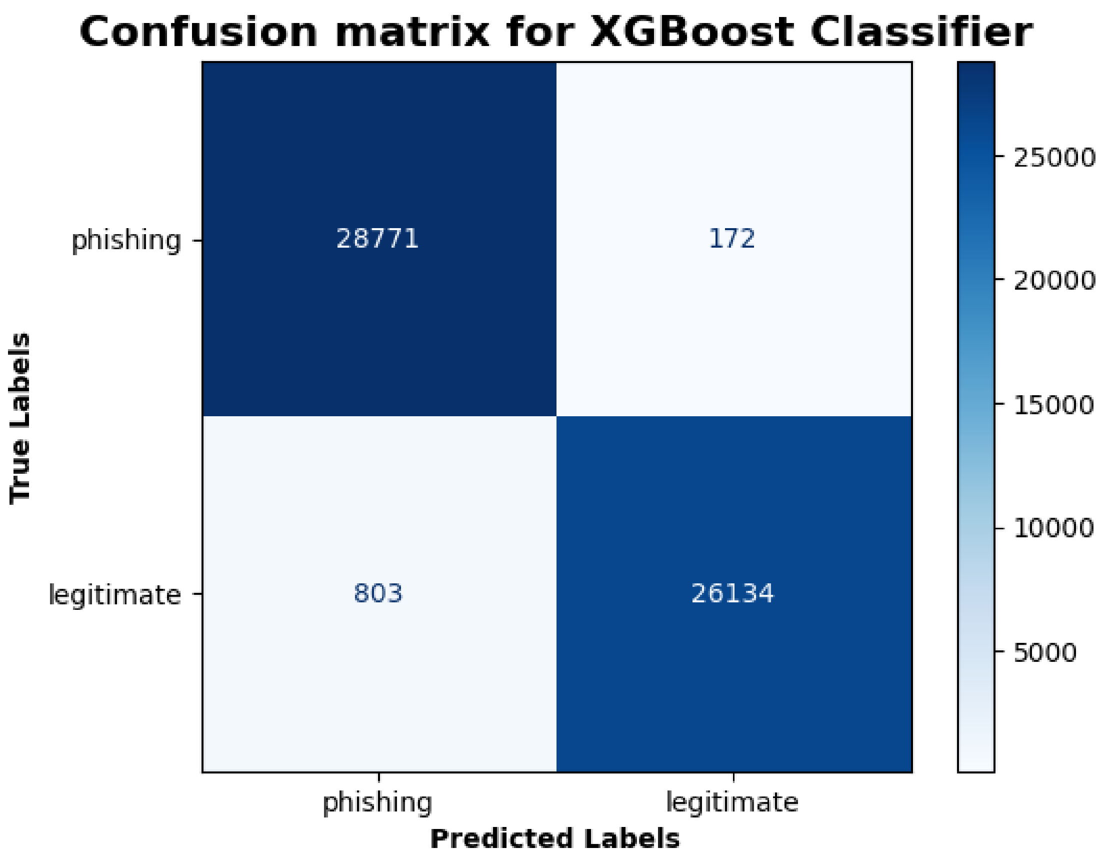
XGBoost Classifier

[8]:
```python
xg_model = XGBClassifier()
xg_model.fit(X_train,y_train)

xg_pred_train = xg_model.predict(X_train)
xg_pred_test = xg_model.predict(X_test)

print('Metrics of XGBoost Classifier on Training data:')
evaluate_model(y_train,xg_pred_train)

print()

print('Metrics of XGBoost Classifier on Testing data:')
evaluate_model(y_test,xg_pred_test)
```

```
Metrics of XGBoost Classifier on Training data:
Accuracy: 0.9858088761632069
Precision: 0.9963655570506935
Recall: 0.974298433311198
F1-Score: 0.9852084434358194

Metrics of XGBoost Classifier on Testing data:
Accuracy: 0.9825518969219756
Precision: 0.9934615677031856
Recall: 0.9701897018970189
F1-Score: 0.9816877335987829
```

By comparing the metrics of Random Forest Classifier & XGBoost Classifier on both training set and testing set, XGBoost Classifier is best. Both the model's metrics are good on training set but on testing set, Random Forest model's metrics are slightly lower than XGBoost model's metrics telling that Random Forest model has less Generalization. Therefore, we prefer XGBoost Classifier.

[9]:
```
disp = ConfusionMatrixDisplay.
  ↪from_estimator(xg_model,X_test,y_test,display_labels=['phishing','legitimate'],cmap=plt.
  ↪cm.Blues)
plt.xlabel('Predicted Labels',weight='bold')
plt.ylabel('True Labels',weight='bold')
plt.title('Confusion matrix for XGBoost Classifier',weight='bold',fontsize=16)
plt.show()
```

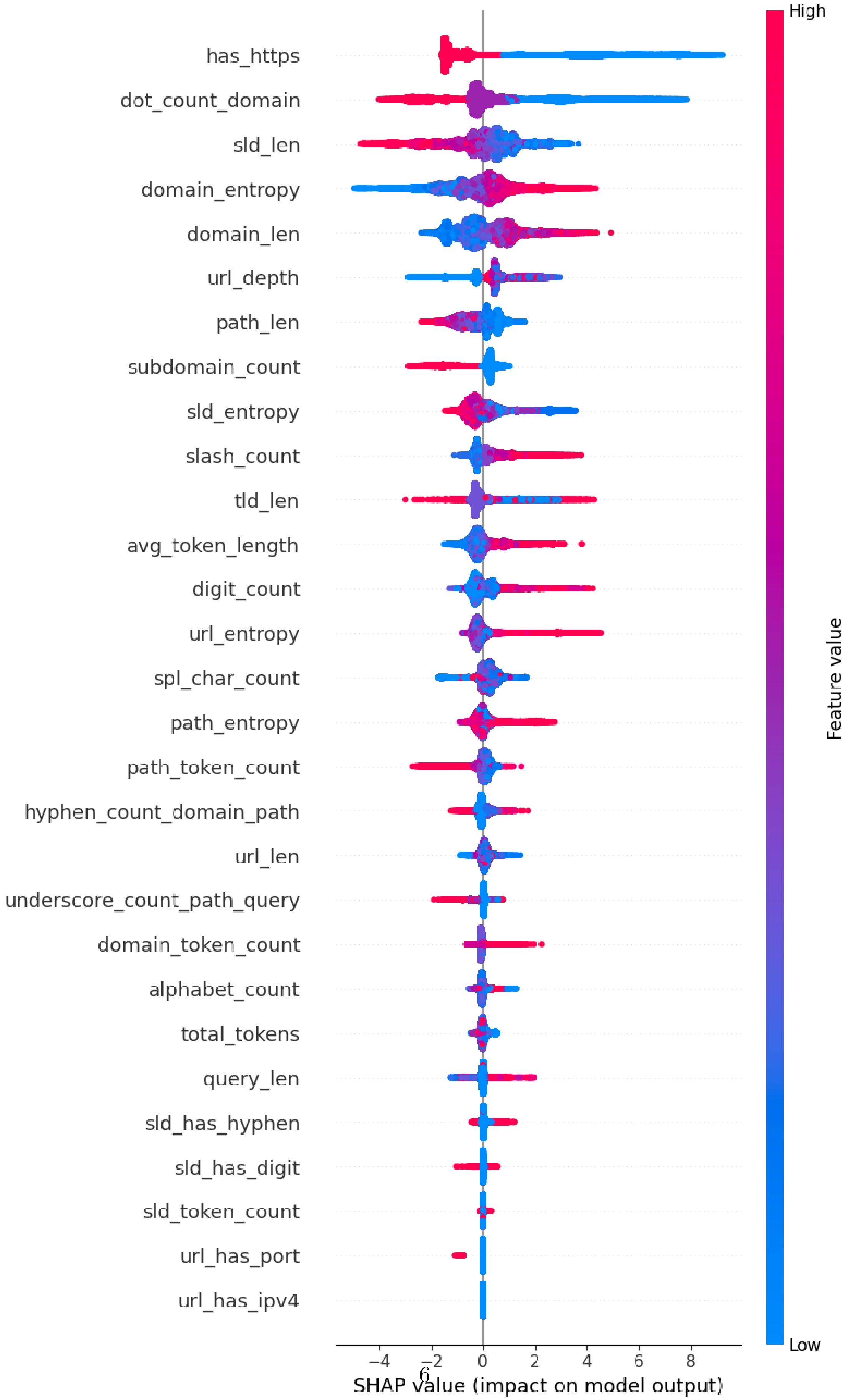


Feature Importance

[10]:
```
features = df.drop(columns='class').columns
explainer = shap.TreeExplainer(xg_model)
shap_values = explainer.shap_values(X_test)

shap.initjs()
```

```
<IPython.core.display.HTML object>
```

[11]:
```
X_test_df = pd.DataFrame(X_test,columns=features)
shap.summary_plot(shap_values,X_test_df,max_display=30)
```



has_https
dot_count_domain
sld_len
domain_entropy
domain_len
url_depth
path_len
subdomain_count
sld_entropy
slash_count
tld_len
avg_token_length
digit_count
url_entropy
spl_char_count
path_entropy
path_token_count
hyphen_count_domain_path
url_len
underscore_count_path_query
domain_token_count
alphabet_count
total_tokens
query_len
sld_has_hyphen
sld_has_digit
sld_token_count
url_has_port
url_has_ipv4
−4 −2 0 2 4 6 8
SHAP value (impact on model output)
High
Low
Feature value

From the above plot, most of the features have some impact in predicting phishing URLs. But there are some features which does not show any impact on predictions: - total_tokens - sld_token_count - url_has_ipv4 - url_has_port

So, we will ignore these features.

Therefore the final features considered to train the model are: - has_https - url_len - domain_len - path_len - query_len - url_depth - subdomain_count - tld_len - sld_len - sld_has_digit - sld_has_hyphen - dot_count_domain - hyphen_count_domain_path - underscore_count_path_query - slash_count - digit_count - alphabet_count - spl_char_count - url_entropy - domain_entropy - sld_entropy - path_entropy - domain_token_count - path_token_count - avg_token_length

[12]:
```
# Updated data
updated_df = df.
 ↪drop(columns=['total_tokens','sld_token_count','url_has_ipv4','url_has_port'])

X_updated = updated_df.drop(columns='class').values
y_updated = updated_df['class']

X_train_updated,X_test_updated,y_train_updated,y_test_updated =␣
 ↪train_test_split(X_updated,y_updated,train_size=0.75,random_state=6)
```

[13]:
```
# Saving the updated data
updated_df.to_csv('data/feature_refined/feature_refined_data.csv',index=False)
print('Updated data saved')
```

```
Updated data saved
```

[14]:
```
model = XGBClassifier()
model.fit(X_train_updated,y_train_updated)
```

[14]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              feature_weights=None, gamma=None, grow_policy=None,
              importance_type=None, interaction_constraints=None,
              learning_rate=None, max_bin=None, max_cat_threshold=None,
              max_cat_to_onehot=None, max_delta_step=None, max_depth=None,
              max_leaves=None, min_child_weight=None, missing=nan,
              monotone_constraints=None, multi_strategy=None, n_estimators=None,
              n_jobs=None, num_parallel_tree=None, …)
```

[15]:
```
print('Metrics of XGBoost Classifier on Training data:')
evaluate_model(y_train_updated,model.predict(X_train_updated))
```

```
print()

print('Metrics of XGBoost Classifier on Testing data:')
evaluate_model(y_test_updated,model.predict(X_test_updated))
```

```
Metrics of XGBoost Classifier on Training data:
Accuracy: 0.9859520400858983
Precision: 0.9962169295544523
Recall: 0.9747411397230625
F1-Score: 0.9853620332788424

Metrics of XGBoost Classifier on Testing data:
Accuracy: 0.9828203292770222
Precision: 0.9936528448177568
Recall: 0.9705609384860971
F1-Score: 0.9819711538461539
```

Hyperparameter Tuning

[16]:
```
search_space = {
    "max_depth" : hp.quniform("max_depth",3,10,1),
    "learning_rate" : hp.loguniform("learning_rate",np.log(0.01),np.log(0.2)),
    "n_estimators" : hp.quniform("n_estimators",100,600,50),
    "subsample" : hp.uniform("subsample",0.6,1.0),
    "colsample_bytree" : hp.uniform("colsample_bytree",0.6,1.0),
    "gamma" : hp.uniform("gamma",0,5),
    "min_child_weight" : hp.qloguniform("min_child_weight",1,10,1),
    "reg_alpha" : hp.loguniform("reg_alpha",np.log(1e-3),np.log(1)),
    "reg_lambda" : hp.loguniform("reg_lambda",np.log(1),np.log(10))
}
```

[17]:
```
def objective(params):

    params['max_depth'] = int(params['max_depth'])
    params['n_estimators'] = int(params['n_estimators'])
    params['min_child_weight'] = int(params['min_child_weight'])

    params.update({
        "objective" : "binary:logistic",
        "eval_metric" : "logloss",
        "random_state" : 42,
        "tree_method" : "hist",
        "n_jobs" : -1
    })

    skf = StratifiedKFold(n_splits=5,shuffle=True,random_state=42)

    recalls = []
```

```
    for train_idx,val_idx in skf.split(X_train,y_train):
        X_tr, X_val = X_train[train_idx], X_train[val_idx]
        y_tr, y_val = y_train[train_idx], y_train[val_idx]

        model = XGBClassifier(**params)
        model.fit(X_tr,y_tr)

        y_pred = model.predict(X_val)
        recalls.append(recall_score(y_val, y_pred))

    mean_recall = np.mean(recalls)
    std_recall = np.std(recalls)

    return {"loss" : -mean_recall, "status" : STATUS_OK}
```

[18]:
```
trials = Trials()

best_params = fmin(
    fn = objective,
    space = search_space,
    algo = tpe.suggest,
    max_evals = 50,
    trials = trials
)
```

```
100%|      | 50/50 [04:07<00:00,  4.96s/trial, best loss:
-0.9702648921764627]
```

[19]:
```
best_params
```

[19]:
```
{'colsample_bytree': 0.6467775791690556,
 'gamma': 1.1327649937229542,
 'learning_rate': 0.19739238497749395,
 'max_depth': 6.0,
 'min_child_weight': 3.0,
 'n_estimators': 300.0,
 'reg_alpha': 0.05223219666480833,
 'reg_lambda': 2.2337823495400113,
 'subsample': 0.6033832013130304}
```

[20]:
```
best_params['max_depth'] = int(best_params['max_depth'])
best_params['n_estimators'] = int(best_params['n_estimators'])
best_params['min_child_weight'] = int(best_params['min_child_weight'])

best_params.update({
    'objective' : 'binary:logistic',
    'eval_metric' : 'logloss',
```

```
    'random_state' : 42,
    'n_jobs' : -1
})

final_model = XGBClassifier(**best_params)
final_model.fit(X_train,y_train)

print('Metrics of XGBoost Classifier on Training data:')
evaluate_model(y_train,final_model.predict(X_train))

print()

print('Metrics of XGBoost Classifier on Testing data:')
evaluate_model(y_test,final_model.predict(X_test))
```

```
Metrics of XGBoost Classifier on Training data:
Accuracy: 0.9871391076115485
Precision: 0.9960149377177373
Recall: 0.9773973781942498
F1-Score: 0.9866183370987364

Metrics of XGBoost Classifier on Testing data:
Accuracy: 0.9824087329992842
Precision: 0.9920376128004853
Recall: 0.9713034116642536
F1-Score: 0.9815610286807601
```

Handling False Negatives

[30]:
```
import numpy as np
from sklearn.metrics import precision_recall_curve, f1_score

def recall_and_threshold_constrained_selection(
    y_true,
    y_prob,
    min_recall=0.9725,
    min_threshold=0.45
):
    precision, recall, thresholds = precision_recall_curve(y_true, y_prob)

    # precision_recall_curve returns one extra precision/recall value
    precision = precision[:-1]
    recall = recall[:-1]

    thresholds = np.array(thresholds)

    # Apply BOTH constraints
    valid_idxs = np.where(
```

```
        (recall >= min_recall) &
        (thresholds >= min_threshold)
    )[0]

    if len(valid_idxs) == 0:
        raise ValueError(
            f"No threshold satisfies recall >= {min_recall} "
            f"and threshold >= {min_threshold}"
        )

    # Among valid thresholds, maximize precision
    best_idx = valid_idxs[np.argmax(precision[valid_idxs])]
    best_threshold = thresholds[best_idx]

    return {
        "threshold": float(best_threshold),
        "precision": float(precision[best_idx]),
        "recall": float(recall[best_idx]),
        "f1": float(
            f1_score(
                y_true,
                (y_prob >= best_threshold).astype(int)
            )
        ),
        "accuracy": accuracy_score(
                y_true,
                (y_prob >= best_threshold).astype(int)
            )
    }
```

[22]:
```
y_prob = final_model.predict_proba(X_test)[:,1]
y_prob
```

[22]:
```
array([0.9997161 , 0.00365725, 0.02950696, …, 0.99990857, 0.9999615 ,
       0.99667823], shape=(55880,), dtype=float32)
```

[31]:
```
recall_and_threshold_constrained_selection(y_test,y_prob)
```

[31]:
```
{'threshold': 0.46429693698883057,
 'precision': 0.9904347826086957,
 'recall': 0.9725284924082117,
 'f1': 0.9813999662839268,
 'accuracy': 0.9822297780959198}
```

After applying a recall-constrined threshold (0.45) slightly increased recall to 0.9725 while maintaining very high precision (0.9904), resulting in a unchanged F1-score (0.9821) and accuracy (0.9822) compared to the initial model. Now the threshold is 0.464.

Saving the model

[32]:
```
with open('models/XGBoostModel.pkl','wb') as file:
    pickle.dump(final_model,file=file)
```