FYP_Classification_Final

February 20, 2025

[1]:
```
from sklearn.model_selection import StratifiedKFold, cross_val_score
from sklearn.metrics import accuracy_score, classification_report, log_loss,␣
↪confusion_matrix
from sklearn.svm import LinearSVC, SVC
from sklearn.tree import DecisionTreeClassifier
from skopt import BayesSearchCV
from skopt import gp_minimize
from skopt.space import Real, Categorical, Integer
from skopt.utils import use_named_args
from cuml.model_selection import train_test_split
from cuml.svm import SVC as cuSVC
from cuml.ensemble import RandomForestClassifier as cuml_RFClassifier
from cuml.neighbors import KNeighborsClassifier as cumlKNeighborsClassifier
from xgboost import XGBClassifier
from sklearn.preprocessing import MinMaxScaler
from sklearn.base import BaseEstimator, ClassifierMixin
import xgboost as xgb
import seaborn as sns
import json
import re
import time
import numpy as np
import cudf
import cupy as cp
from urllib.parse import urlparse
import pandas as pd
import matplotlib.pyplot as plt
import os
import pickle
import tkinter as tk
import customtkinter as ctk
# Set CUDA device
os.environ["CUDA_VISIBLE_DEVICES"] = "0"
```

[2]:
```
def count_special_chars(url):
    # Implement your logic to count special characters
    special_chars = re.findall(r'[!@#\$%\^&\*\(\)\-\+=]', url)
```

```
    return len(special_chars)

def check_url(url, words):
    # Check if URL contains a hyphen
    result = 0
    contains_hyphen = '-' in url

    # Check if URL contains any word from the list
    contains_word = any(re.search(rf'\b{word}\b', url) for word in words)

    # Return 1 if both conditions are met, else return 0
    if contains_hyphen and contains_word:
        result = 1
    else:
        result = 0
    return result

def extract_features(url):
    features = {}
    parsed_url = urlparse(url)
    domain = parsed_url.netloc
    features['url_length'] = len(url)
    features['num_digits'] = sum(char.isdigit() for char in url)
    features['num_letters'] = sum(char.isalpha() for char in url)
    features['num_dots'] = url.count(".")
    features['url_depth'] = url.count("/")
    features['contains_https'] = 0 if "https" in url else 1
    features['contains_dash'] = 1 if "-" in url else 0
    features['num_subdomains'] = len(url.split('.')) - 2
    features['num_special_chars'] = count_special_chars(url)
    # Prefix and Suffix lengths
    try:
        if domain in url:
            parts = url.split(domain)
            features['prefix_length'] = len(parts[0])
            features['suffix_length'] = len(parts[1]) if len(parts) > 1 else 0
        else:
            features['prefix_length'] = 0
            features['suffix_length'] = 0
    except:
        features['prefix_length'] = 0
        features['suffix_length'] = 0
    return features
```

[3]:
```
def preprocess_data(df):
    # Handling missing values (NaNs)
    # Ensure numeric columns before filling NaNs with mean
```

```python
    numeric_columns = df.select_dtypes(include=np.number).columns.tolist()
    df[numeric_columns] = df[numeric_columns].fillna(df[numeric_columns].mean())

    # Handling outliers using box plots or other methods
    # Example:
    Q1 = df[numeric_columns].quantile(0.25)
    Q3 = df[numeric_columns].quantile(0.75)
    IQR = Q3 - Q1
    df = df[~((df[numeric_columns] < (Q1 - 1.5 * IQR)) | (df[numeric_columns] >
 ↪(Q3 + 1.5 * IQR))).any(axis=1)]

    return df
```

[4]:
```python
# Plot histograms for features
def plot_histograms(df):
    df.hist(figsize=(12, 10))
    plt.tight_layout()
    plt.show()

def plot_boxplot(df):
    # Box plot to find outliers
    plt.figure(figsize=(10, 6))
    sns.boxplot(data=df)
    plt.show()

# Plot heatmap for feature correlations
def plot_heatmap(df):
    plt.figure(figsize=(12, 10))
    sns.heatmap(df.corr(), annot=True, cmap='coolwarm', fmt=".2f")
    plt.title('Correlation Heatmap of Features')
    plt.show()
```

[5]:
```python
def process_csv(filename):
    # Read the CSV file
    df = pd.read_csv(filename)

    # Extract 'label' column
    labels = df['label']
    df.drop(columns=['label'], inplace=True)
    processing_list = df['url'].tolist()
    processing_features = [extract_features(url) for url in processing_list]
    processing_df = pd.DataFrame(processing_features)

    # Append 'label' column back to the DataFrame
    processing_df['label'] = labels
    return processing_df
```

[6]:
```python
file1 = 'combined_data5.csv'
processed_data = process_csv(file1)
df = processed_data
```

[7]:
```python
if 'label' in df.columns:
    # Count the occurrences of each value in the 'label' column
    counts = df['label'].value_counts()

    # Print the counts
    print("Count of 1s: ", counts.get(1, 0))
    print("Count of 0s: ", counts.get(0, 0))
else:
    print("'label' column not found in the DataFrame.")
```

```
Count of 1s:  198359
Count of 0s:  174890
```

[8]:
```python
# Perform preprocessing
df = preprocess_data(df)
print(len(df))
print(df.head())
print(df.info())
print(df.describe())
```

```
291471
   url_length  num_digits  num_letters  num_dots  url_depth  contains_https  \
1          48           0           39         3          3               0
2          59           0           47         3          5               1
3          45           5           31         3          5               0
4          43           0           34         2          4               1
5          38           0           32         2          3               1

   contains_dash  num_subdomains  num_special_chars  prefix_length  \
1              1               2                  2              8
2              0               2                  0              7
3              0               2                  0              8
4              0               1                  0              7
5              0               1                  0              7

   suffix_length  label
1             23      0
2             35      0
3             24      0
4             22      0
5              4      0
<class 'pandas.core.frame.DataFrame'>
Index: 291471 entries, 1 to 373248
Data columns (total 12 columns):
```

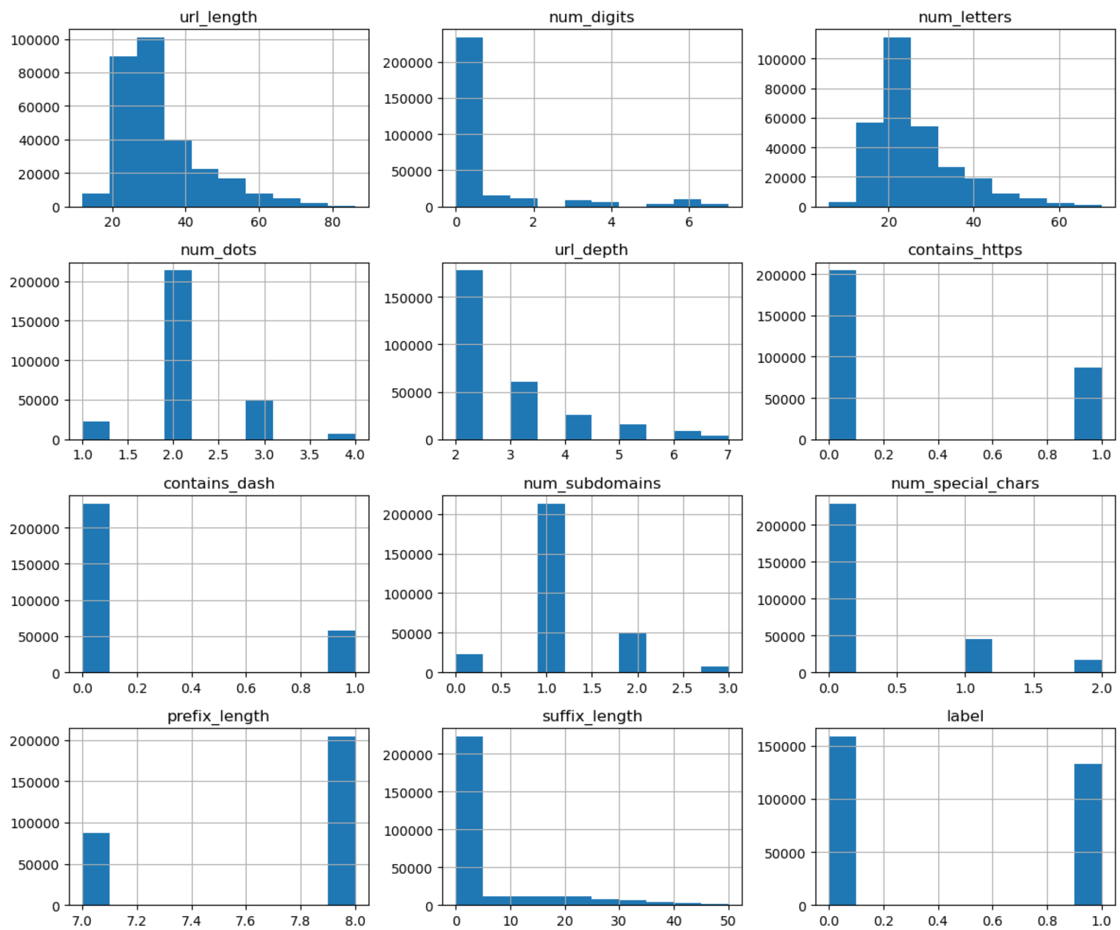
```
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   url_length         291471 non-null  int64
 1   num_digits         291471 non-null  int64
 2   num_letters        291471 non-null  int64
 3   num_dots           291471 non-null  int64
 4   url_depth          291471 non-null  int64
 5   contains_https     291471 non-null  int64
 6   contains_dash      291471 non-null  int64
 7   num_subdomains     291471 non-null  int64
 8   num_special_chars  291471 non-null  int64
 9   prefix_length      291471 non-null  int64
 10  suffix_length      291471 non-null  int64
 11  label              291471 non-null  int64
dtypes: int64(12)
memory usage: 28.9 MB
None
          url_length     num_digits    num_letters       num_dots  \
count  291471.000000  291471.000000  291471.000000  291471.000000
mean       32.887862       0.645457      26.048732       2.139592
std        11.337166       1.562661       9.795529       0.565579
min        12.000000       0.000000       6.000000       1.000000
25%        25.000000       0.000000      19.000000       2.000000
50%        30.000000       0.000000      24.000000       2.000000
75%        38.000000       0.000000      30.000000       2.000000
max        86.000000       7.000000      70.000000       4.000000

          url_depth  contains_https  contains_dash  num_subdomains  \
count  291471.00000   291471.000000  291471.000000   291471.000000
mean        2.72293        0.299337       0.199251        1.139592
std         1.13714        0.457968       0.399438        0.565579
min         2.00000        0.000000       0.000000        0.000000
25%         2.00000        0.000000       0.000000        1.000000
50%         2.00000        0.000000       0.000000        1.000000
75%         3.00000        1.000000       0.000000        1.000000
max         7.00000        1.000000       1.000000        3.000000

       num_special_chars  prefix_length  suffix_length          label
count      291471.000000  291471.000000  291471.000000  291471.000000
mean            0.271193       7.700560       5.057687       0.455428
std             0.558772       0.458013      10.125704       0.498010
min             0.000000       7.000000       0.000000       0.000000
25%             0.000000       7.000000       0.000000       0.000000
50%             0.000000       8.000000       0.000000       0.000000
75%             0.000000       8.000000       1.000000       1.000000
max             2.000000       8.000000      50.000000       1.000000
```

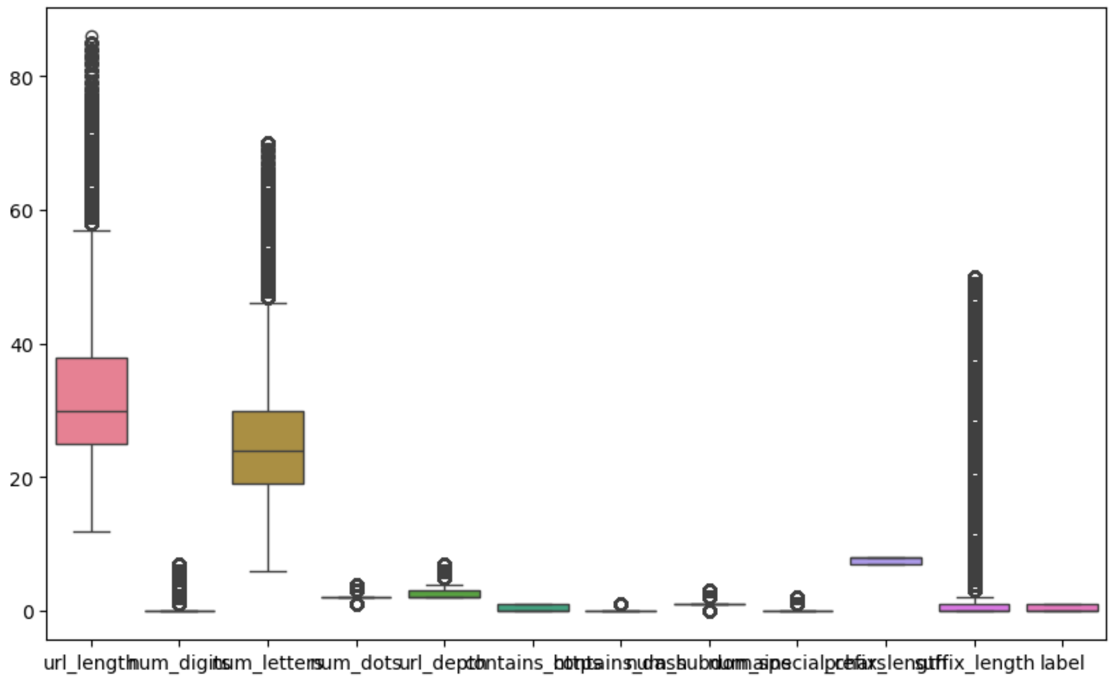
[9]:

```
# Plot histograms for features
plt.rcParams['figure.figsize'] = [20, 20]
plot_histograms(df)
```

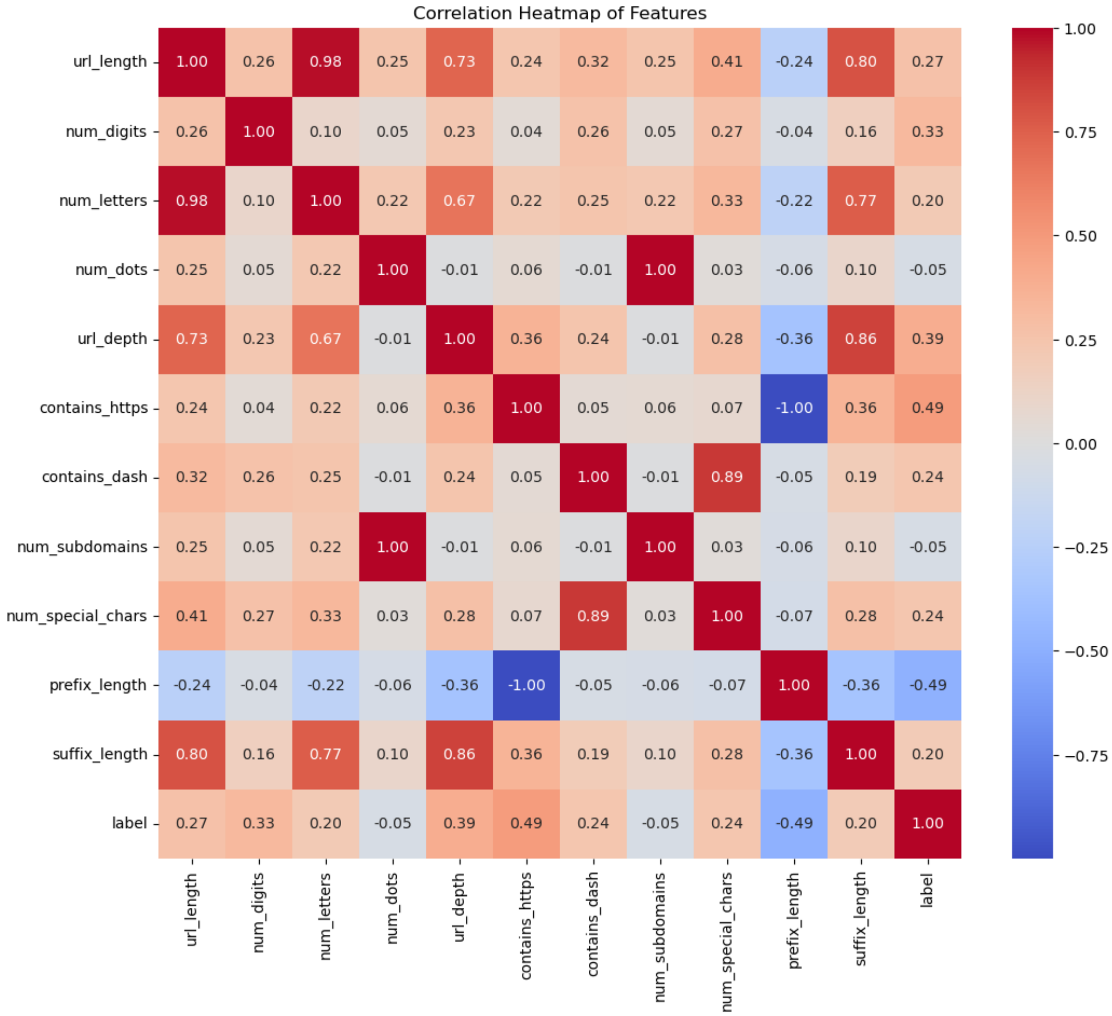


[10]:

```
# Plot boxplot for features
plot_boxplot(df)
```



[11]:
```
# Plot heatmap for features
plot_heatmap(df)
```




```
[12]: # Prepare data for model training
X = df.drop('label', axis=1).values
y = df['label'].values

# Scale data if necessary
scaler = MinMaxScaler(feature_range=(-1,1))
X = scaler.fit_transform(X)

# Convert features to float32 for compatibility
X = X.astype(np.float32)
```

```
[13]: # Train-test-validate split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

```
X_test, X_validate, y_test, y_validate = train_test_split(X_test, y_test,␣
↪test_size=0.5, random_state=42)

# Convert to DataFrame/Series for .iloc usage
X_train, y_train = pd.DataFrame(X_train), pd.Series(y_train)
X_validate, y_validate = pd.DataFrame(X_validate), pd.Series(y_validate)
X_test, y_test = pd.DataFrame(X_test), pd.Series(y_test)
```

[14]:
```
X_train_gpu = cudf.DataFrame.from_pandas(X_train)
y_train_gpu = cudf.Series(y_train)
X_validate_gpu = cudf.DataFrame.from_pandas(X_validate)
y_validate_gpu = cudf.Series(y_validate)
X_test_gpu = cudf.DataFrame.from_pandas(X_test)
y_test_gpu = cudf.Series(y_test)
```

[15]:
```
# Stratified K-Fold Cross Validation
skf = StratifiedKFold(n_splits=5)
search_space = {
    'svm': [
        Real(1e-6, 1e+6, "log-uniform", name='C'),
    ],
    'random_forest': [
        Integer(10, 500, name='n_estimators'),
        Integer(1, 30, name='max_depth')
    ],
    'gradient_boosting': [
        Integer(10, 500, name='n_estimators'),
        Real(0.01, 1.0, name='learning_rate'),
        Integer(1, 30, name='max_depth')
    ],
    'knn': [
        Integer(1, 20, name='n_neighbors'),
    ]
}
patience = 5  # Number of epochs with no improvement after which training will␣
↪be stopped
min_delta = 0.001  # Minimum change to qualify as an improvement
max_epochs = 50
```

[16]:
```
# Evaluate the models on the training, validation, and test sets
def evaluate_model(model, X, y):
    y_pred = model.predict(X)
    y_cpu = cp.asnumpy(y)
    y_pred_cpu = cp.asnumpy(y_pred)
    accuracy = accuracy_score(y_cpu, y_pred_cpu)
    conf_matrix = confusion_matrix(y_cpu, y_pred_cpu)
    return accuracy, conf_matrix
```

[17]:
```
def plot_confusion_matrix(cm, title):
    plt.figure(figsize=(10, 7))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
    plt.title(title)
    plt.ylabel('Actual')
    plt.xlabel('Predicted')
    plt.show()
```

[18]:
```
def optimize_svm(params):
    params = {k: v for k, v in zip(['C'], params)}
    model = LinearSVC(**params)
    scores = []
    for train_idx, val_idx in skf.split(X_train, y_train):
        X_train_fold, X_val_fold = X_train.iloc[train_idx], X_train.
 ↪iloc[val_idx]
        y_train_fold, y_val_fold = y_train.iloc[train_idx], y_train.
 ↪iloc[val_idx]
        model.fit(X_train_fold.values, y_train_fold.values)
        y_pred = model.predict(X_val_fold.values)
        scores.append(accuracy_score(y_val_fold.values, y_pred))
    return -np.mean(scores)
```

[19]:
```
def optimize_rf(params):
    params = {k: v for k, v in zip(['n_estimators', 'max_depth'], params)}
    model = cuml_RFClassifier(**params)
    scores = []
    for train_idx, val_idx in skf.split(X_train, y_train):
        X_train_fold, X_val_fold = X_train.iloc[train_idx], X_train.
 ↪iloc[val_idx]
        y_train_fold, y_val_fold = y_train.iloc[train_idx], y_train.
 ↪iloc[val_idx]
        model.fit(X_train_fold.values, y_train_fold.values)
        y_pred = model.predict(X_val_fold.values)
        scores.append(accuracy_score(y_val_fold.values, y_pred))
    return -np.mean(scores)
```

[20]:
```
def optimize_xgb(params):
    params = {k: v for k, v in zip(['n_estimators', 'learning_rate',␣
 ↪'max_depth'], params)}
    model = xgb.XGBClassifier(device = "cuda", **params)
    scores = []
    for train_idx, val_idx in skf.split(X_train, y_train):
        X_train_fold, X_val_fold = X_train.iloc[train_idx], X_train.
 ↪iloc[val_idx]
        y_train_fold, y_val_fold = y_train.iloc[train_idx], y_train.
 ↪iloc[val_idx]
```

```
        model.fit(X_train_fold.values, y_train_fold.values)
        y_pred = model.predict(X_val_fold.values)
        scores.append(accuracy_score(y_val_fold.values, y_pred))
    return -np.mean(scores)
```

[21]:
```
def optimize_knn(params):
    params = {k: v for k, v in zip(['n_neighbors', 'weights'], params)}
    # model = cumlKNeighborsClassifier(**params, weights='uniform')
    model = cumlKNeighborsClassifier(**params)
    scores = []
    for train_idx, val_idx in skf.split(X_train, y_train):
        X_train_fold, X_val_fold = X_train.iloc[train_idx], X_train.
 ↪iloc[val_idx]
        y_train_fold, y_val_fold = y_train.iloc[train_idx], y_train.
 ↪iloc[val_idx]
        model.fit(X_train_fold.values, y_train_fold.values)
        y_pred = model.predict(X_val_fold.values)
        scores.append(accuracy_score(y_val_fold.values, y_pred))
    return -np.mean(scores)
```

[22]:
```
start_time = time.time()
# Retrieve and train best SVM models
opt_svm = gp_minimize(optimize_svm, search_space['svm'], n_calls=32,␣
 ↪random_state=42)
best_svm = LinearSVC(C=opt_svm.x[0])
best_svm.fit(X_train.values, y_train.values)
y_pred_svm = best_svm.predict(X_validate.values)

# Print accuracy reports
print("Validation Accuracy for SVM:", accuracy_score(y_validate.values,␣
 ↪y_pred_svm))
print("Classification Report for SVM:\n", classification_report(y_validate.
 ↪values, y_pred_svm))
end_time = time.time()
total_time = end_time - start_time
print(f"Total Time: {total_time:.4f} seconds")
```

```
Validation Accuracy for SVM: 0.8730229526194806
Classification Report for SVM:
               precision    recall  f1-score   support

           0       0.87      0.91      0.89     15904
           1       0.88      0.83      0.86     13243

    accuracy                           0.87     29147
   macro avg       0.87      0.87      0.87     29147
weighted avg       0.87      0.87      0.87     29147
```

Total Time: 104.6698 seconds

[23]:
```
best_svm_params = dict(zip(['C'], opt_svm.x))
best_svm = LinearSVC(**best_svm_params, random_state=42)
best_svm.fit(X_train_gpu.to_numpy(), y_train_gpu.to_numpy())
```

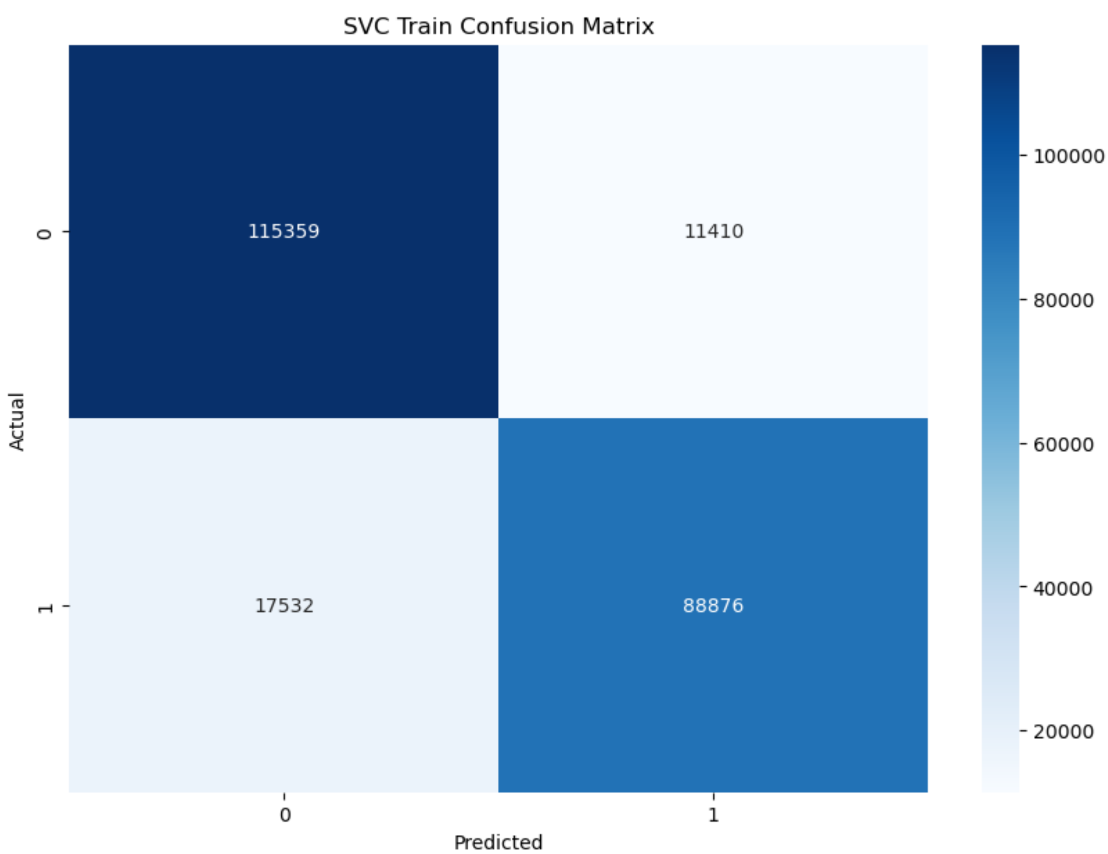
[23]: LinearSVC(C=64.66386742396142, random_state=42)

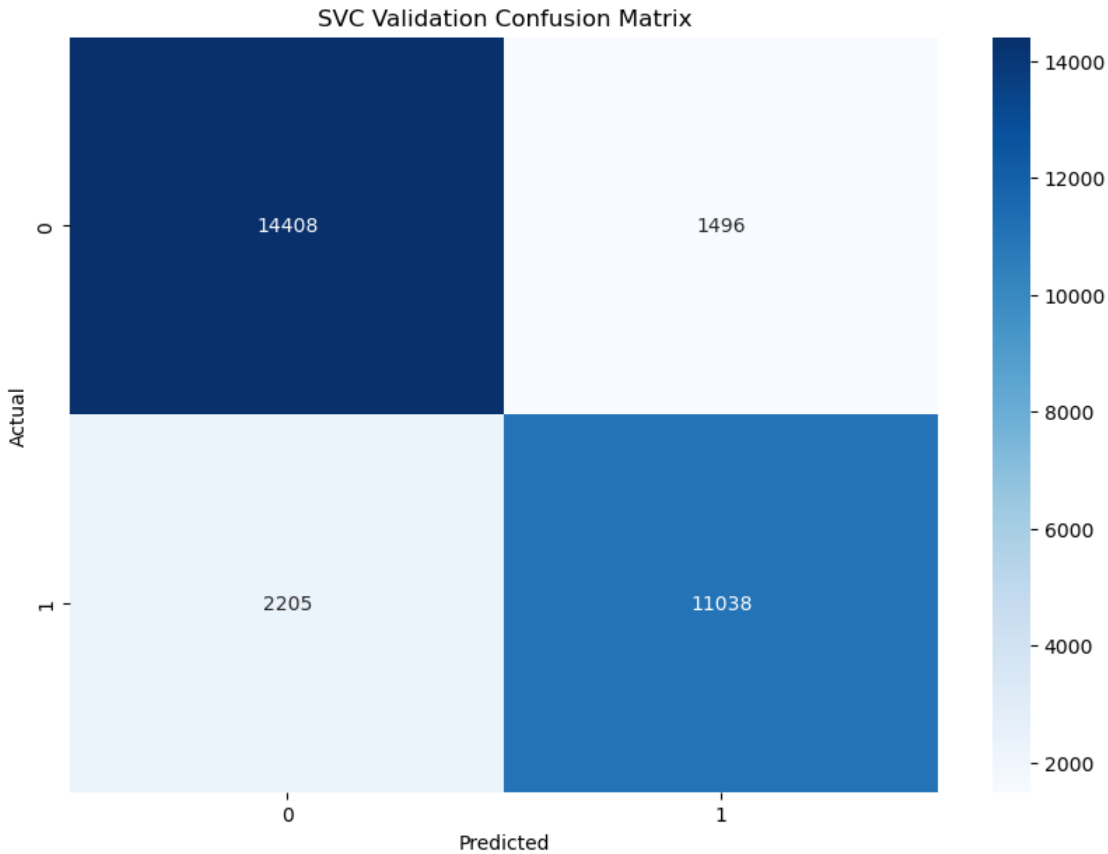
[24]:
```
svm_train_accuracy, svc_train_cm = evaluate_model(best_svm, X_train, y_train)
svm_val_accuracy, svc_val_cm = evaluate_model(best_svm, X_validate, y_validate)
svm_test_accuracy, svc_test_cm = evaluate_model(best_svm, X_test, y_test)
```

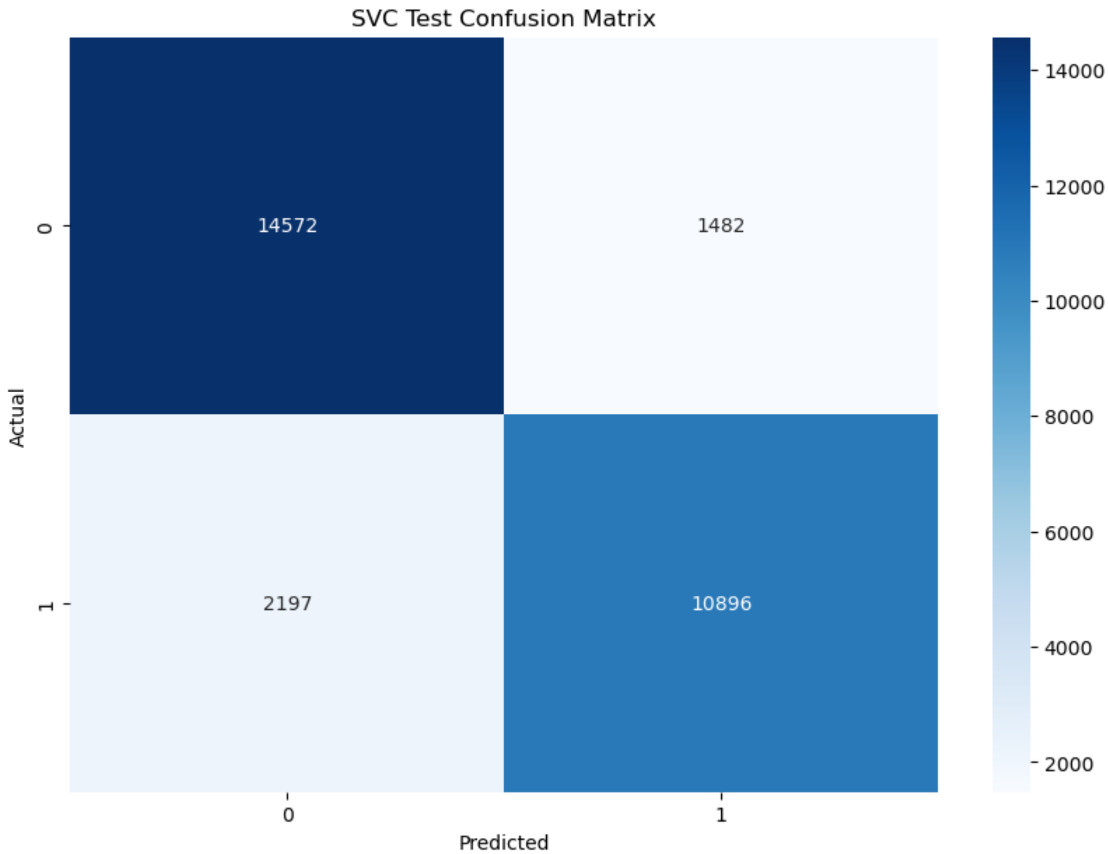
[25]:
```
print(f'SVM - Training Accuracy: {svm_train_accuracy}, Validation Accuracy:␣
↪{svm_val_accuracy}, Test Accuracy: {svm_test_accuracy}')
```

SVM - Training Accuracy: 0.8758796965395387, Validation Accuracy: 0.8730229526194806, Test Accuracy: 0.8737777472810238

[26]:
```
plot_confusion_matrix(svc_train_cm, 'SVC Train Confusion Matrix')
plot_confusion_matrix(svc_val_cm, 'SVC Validation Confusion Matrix')
plot_confusion_matrix(svc_test_cm, 'SVC Test Confusion Matrix')
```




SVC Validation Confusion Matrix
14408
1496
2205
11038
0
1
Actual
Predicted
14000
12000
10000
8000
6000
4000
2000



[27]:

```
start_time = time.time()
# Retrieve and train best RF models
opt_rf = gp_minimize(optimize_rf, search_space['random_forest'], n_calls=32,␣
↪random_state=42)
best_rf = cuml_RFClassifier(n_estimators=opt_rf.x[0], max_depth=opt_rf.x[1])
best_rf.fit(X_train, y_train)
y_pred_rf = best_rf.predict(X_validate)

# Print accuracy reports
print("Validation Accuracy for Random Forest:", accuracy_score(y_validate.
↪values, y_pred_rf))
print("Classification Report for Random Forest:\n",␣
↪classification_report(y_validate.values, y_pred_rf))
end_time = time.time()
total_time = end_time - start_time
print(f"Total Time: {total_time:.4f} seconds")
```

```
Validation Accuracy for Random Forest: 0.9456890932171407
Classification Report for Random Forest:
               precision    recall  f1-score   support
```

```
             0       0.96      0.94      0.95     15904
             1       0.93      0.95      0.94     13243

      accuracy                           0.95     29147
     macro avg       0.94      0.95      0.95     29147
  weighted avg       0.95      0.95      0.95     29147

Total Time: 485.6410 seconds
```

[28]:
```
best_rf_params = dict(zip(['n_estimators', 'max_depth'], opt_rf.x))
best_rf = cuml_RFClassifier(**best_rf_params, n_streams=1, random_state=42)
best_rf.fit(X_train_gpu, y_train_gpu)
```

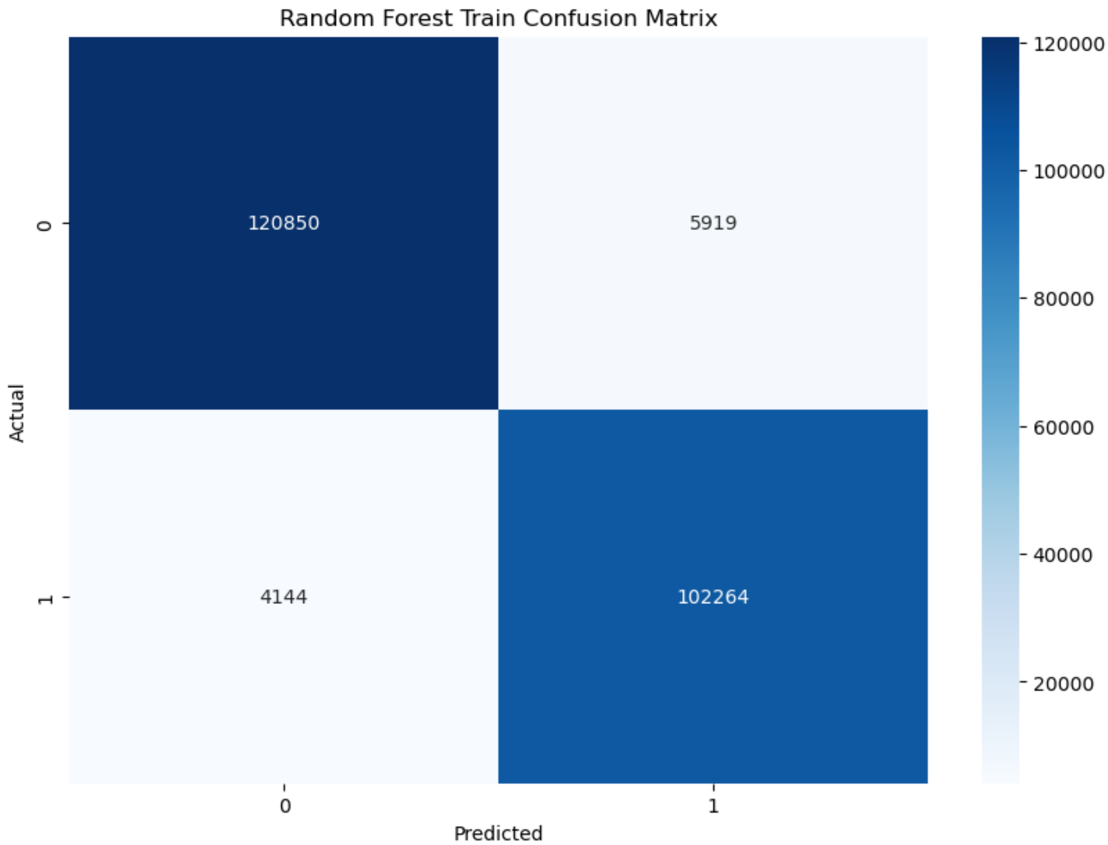
[28]:
```
RandomForestClassifier()
```

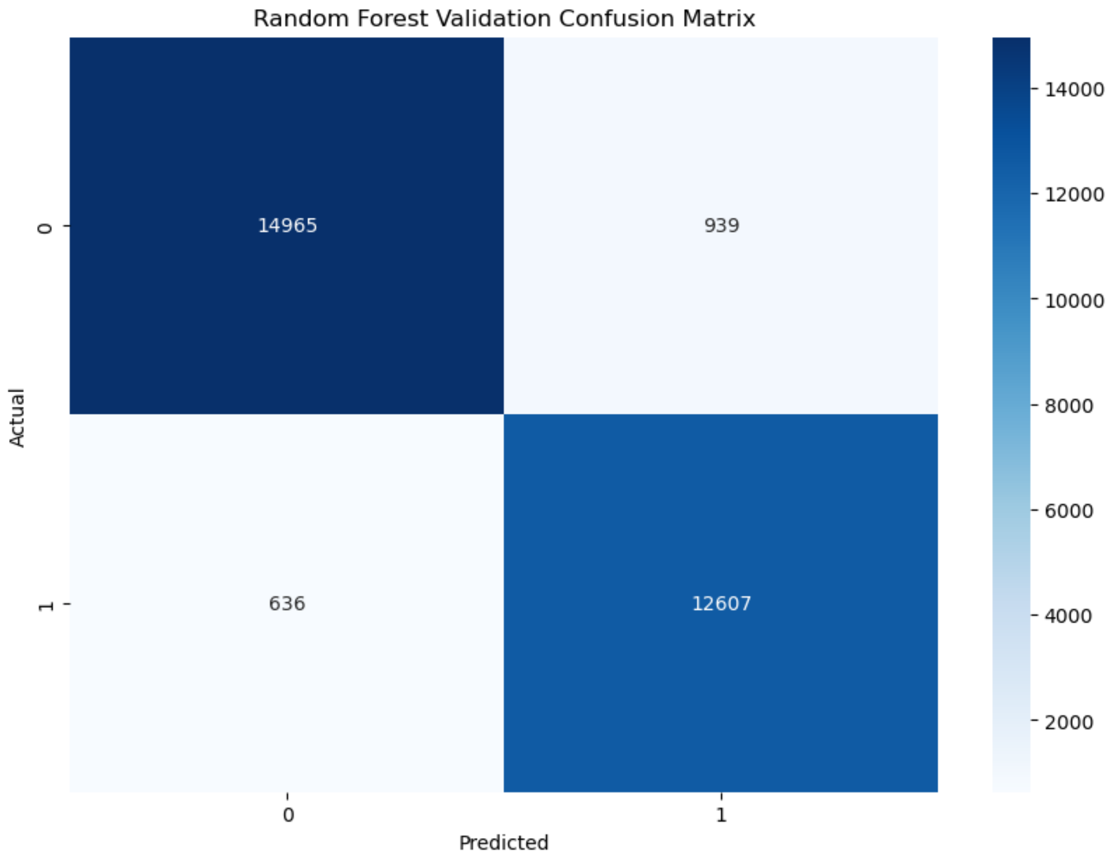
[29]:
```
rf_train_accuracy, rf_train_cm = evaluate_model(best_rf, X_train, y_train)
rf_val_accuracy, rf_val_cm = evaluate_model(best_rf, X_validate, y_validate)
rf_test_accuracy, rf_test_cm = evaluate_model(best_rf, X_test, y_test)
```

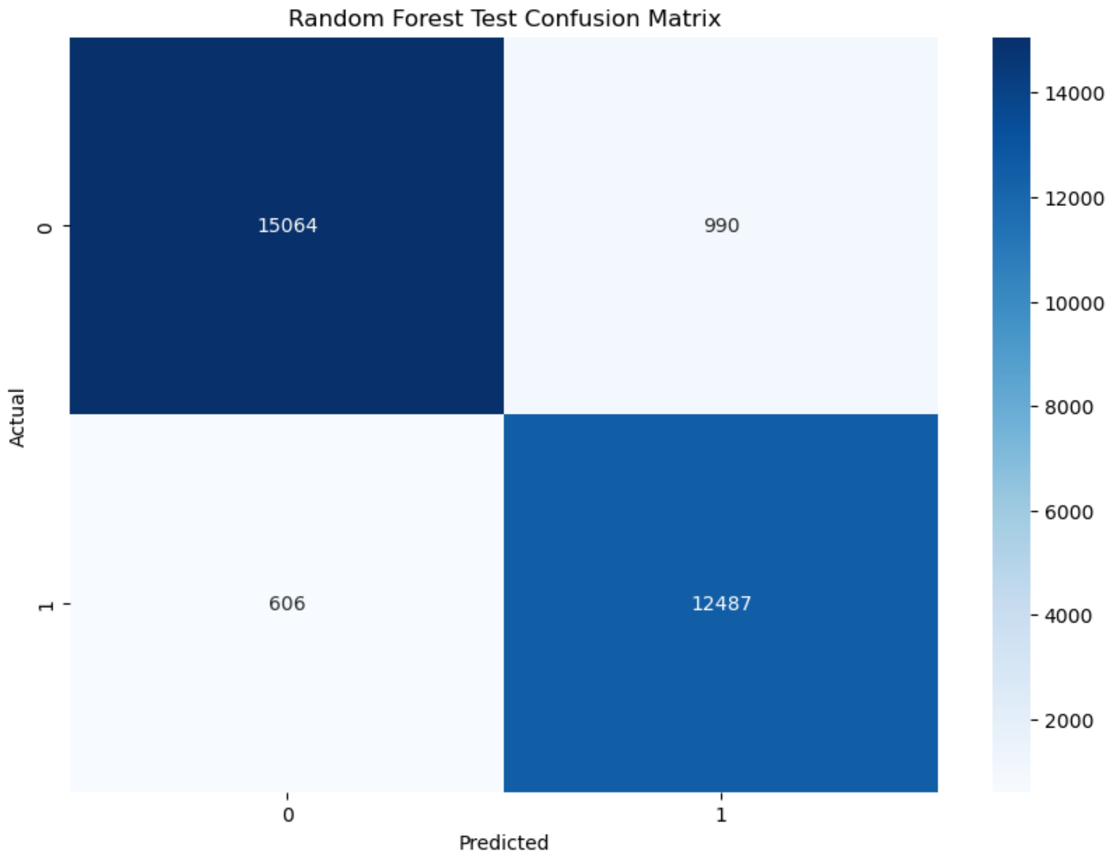
[30]:
```
print(f'Random Forest - Training Accuracy: {rf_train_accuracy}, Validation␣
↪Accuracy: {rf_val_accuracy}, Test Accuracy: {rf_test_accuracy}')
```

```
Random Forest - Training Accuracy: 0.9568439425843887, Validation Accuracy:
0.9459635640031564, Test Accuracy: 0.9452430781898652
```

[31]:
```
plot_confusion_matrix(rf_train_cm, 'Random Forest Train Confusion Matrix')
plot_confusion_matrix(rf_val_cm, 'Random Forest Validation Confusion Matrix')
plot_confusion_matrix(rf_test_cm, 'Random Forest Test Confusion Matrix')
```


Random Forest Train Confusion Matrix
120850
5919
4144
102264
Actual
0
1
Predicted
0
1
120000
100000
80000
60000
40000
20000


Random Forest Validation Confusion Matrix
14965
939
636
12607
Actual
Predicted
0
1
14000
12000
10000
8000
6000
4000
2000



[32]:
```
start_time = time.time()
# Retrieve and train best GB models
opt_xgb = gp_minimize(optimize_xgb, search_space['gradient_boosting'],␣
↪n_calls=32, random_state=42)
best_xgb = xgb.XGBClassifier(device = "cuda", n_estimators=opt_xgb.x[0],␣
↪learning_rate=opt_xgb.x[1], max_depth=opt_xgb.x[2])
best_xgb.fit(cp.array(X_train), y_train)
y_pred_xgb = best_xgb.predict(X_validate)

# Print accuracy reports
print("Validation Accuracy for Gradient Boosting:", accuracy_score(y_validate.
↪values, y_pred_xgb))
print("Classification Report for Gradient Boosting:\n",␣
↪classification_report(y_validate.values, y_pred_xgb))
end_time = time.time()
total_time = end_time - start_time
print(f"Total Time: {total_time:.4f} seconds")
```

```
/home/asdf/miniconda3/envs/rapids-24.06/lib/python3.10/site-
packages/xgboost/core.py:160: UserWarning: [12:21:50] WARNING:
```

```
/home/conda/feedstock_root/build_artifacts/xgboost-
split_1717022039546/work/src/common/error_msg.cc:58: Falling back to prediction
using DMatrix due to mismatched devices. This might lead to higher memory usage
and slower performance. XGBoost is running on: cuda:0, while the input data is
on: cpu.
Potential solutions:
- Use a data structure that matches the device ordinal in the booster.
- Set the device for booster before call to inplace_predict.

This warning will only be shown once.

  warnings.warn(smsg, UserWarning)
```

```
Validation Accuracy for Gradient Boosting: 0.9529282601983051
Classification Report for Gradient Boosting:
              precision    recall  f1-score   support

           0       0.96      0.96      0.96     15904
           1       0.95      0.95      0.95     13243

    accuracy                           0.95     29147
   macro avg       0.95      0.95      0.95     29147
weighted avg       0.95      0.95      0.95     29147

Total Time: 1057.8054 seconds
```

[33]:

```
best_xgb_params = dict(zip(['n_estimators', 'learning_rate', 'max_depth'],␣
  ↪opt_xgb.x))
best_xgb = xgb.XGBClassifier(**best_xgb_params, random_state=42)
best_xgb.fit(X_train_gpu, y_train_gpu)
```

```
/home/asdf/miniconda3/envs/rapids-24.06/lib/python3.10/site-
packages/xgboost/data.py:849: FutureWarning: RangeIndex.format is deprecated and
will be removed in a future version. Convert using index.astype(str) or
index.map(formatter) instead.
  feature_names = data.columns.format()
```

[33]:

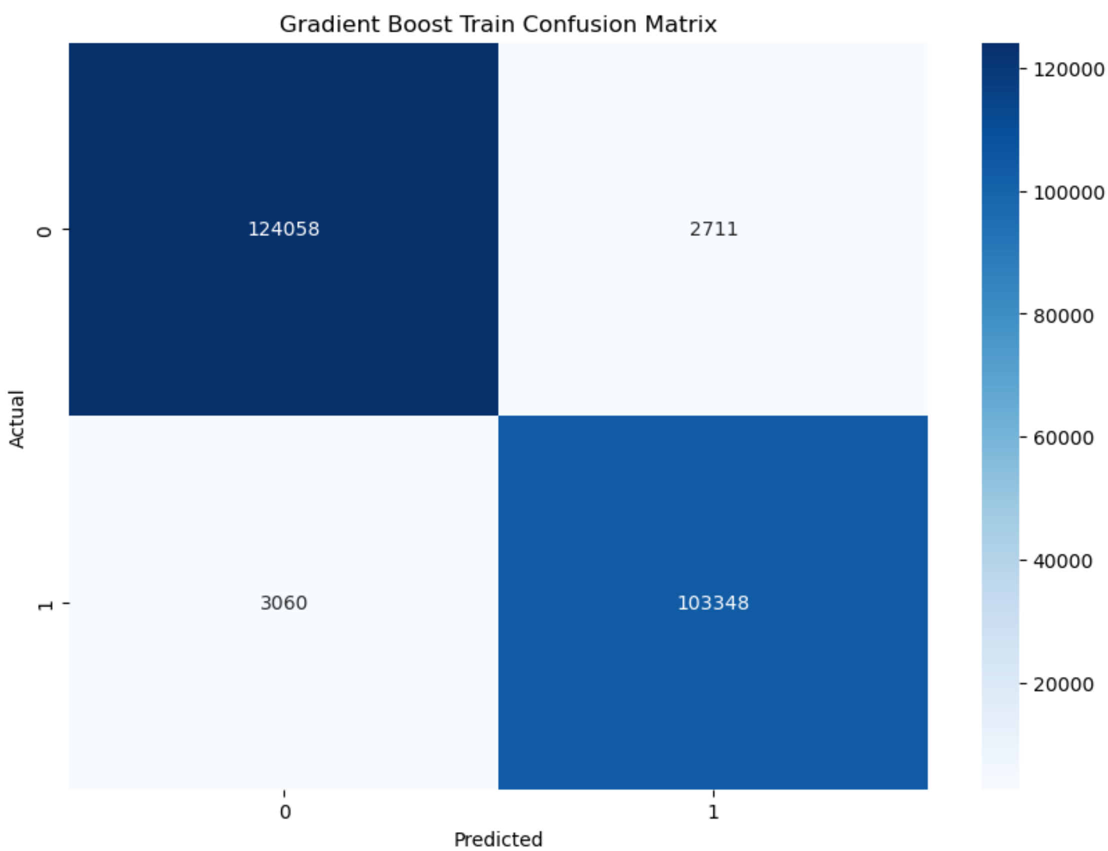
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.06584746323682926,
              max_bin=None, max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=22, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=329, n_jobs=None,
              num_parallel_tree=None, random_state=42, …)
```

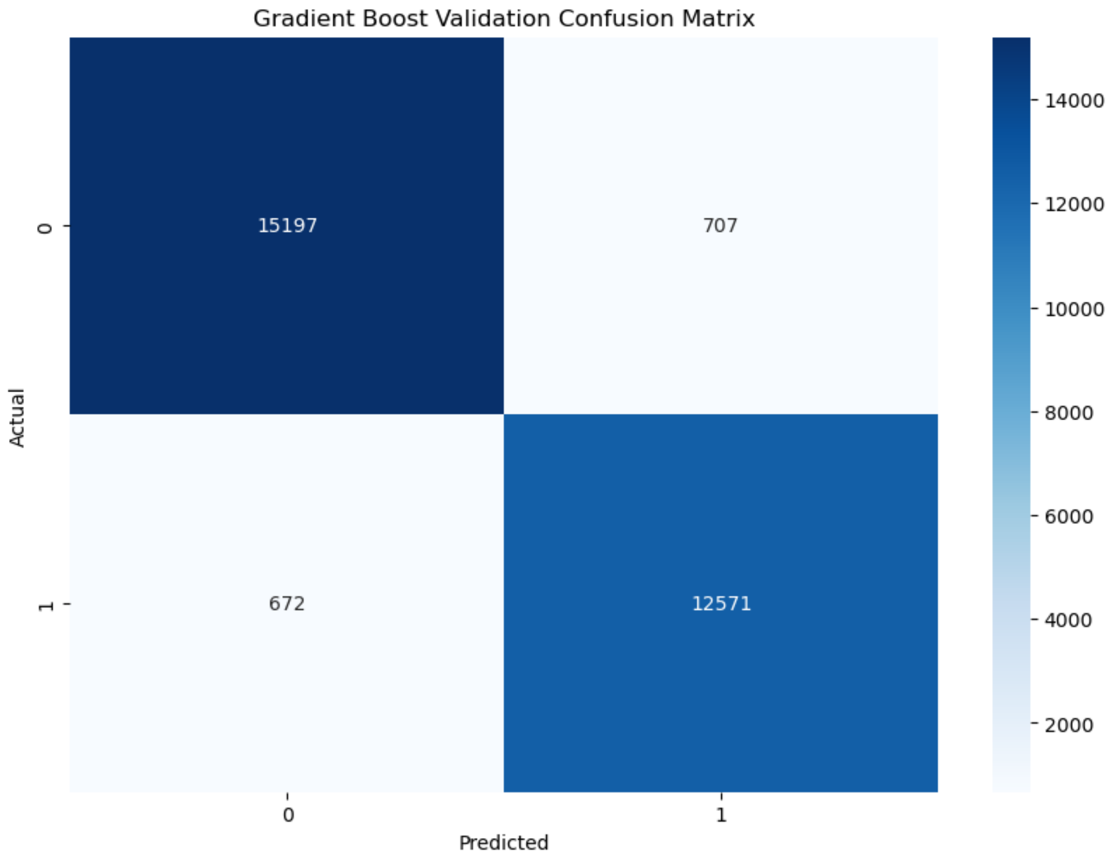
[34]:
```
xgb_train_accuracy, xgb_train_cm = evaluate_model(best_xgb, X_train.values,
    ↪y_train.values)
xgb_val_accuracy, xgb_val_cm = evaluate_model(best_xgb, X_validate.values,
    ↪y_validate.values)
xgb_test_accuracy, xgb_test_cm = evaluate_model(best_xgb, X_test.values, y_test.
    ↪values)
```

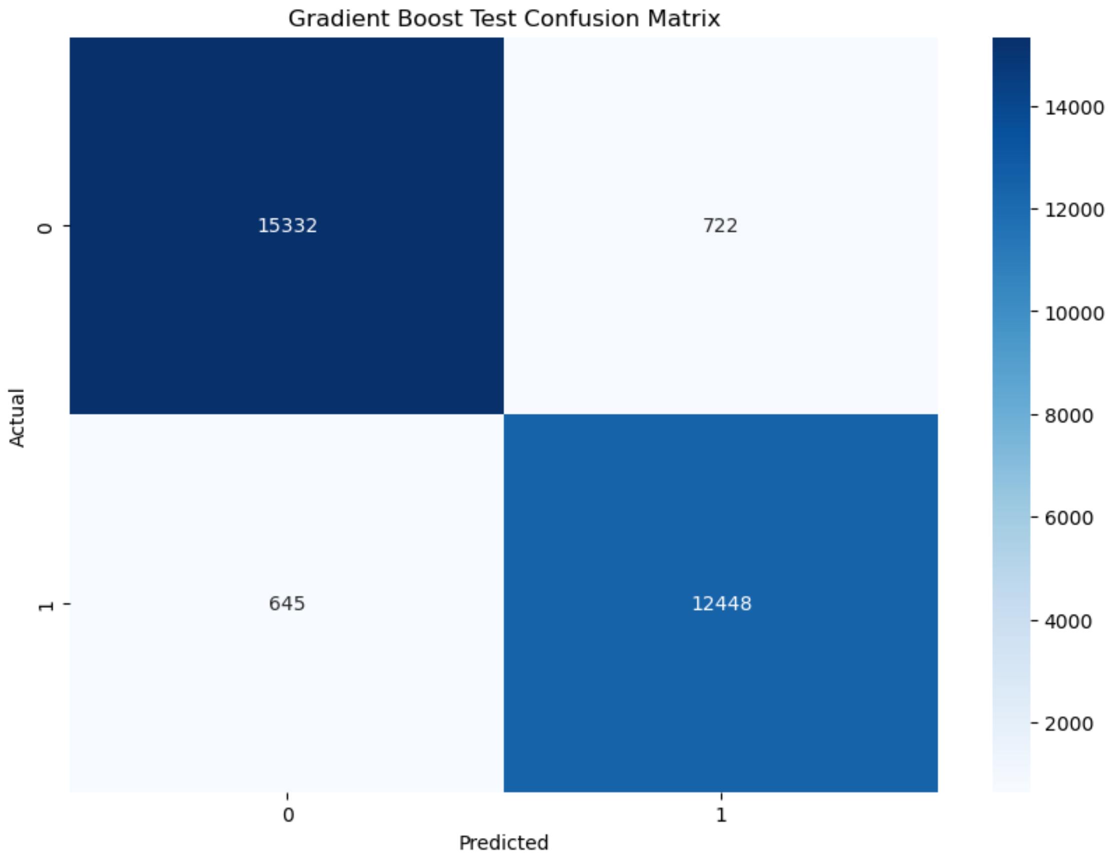
[35]:
```
print(f'XGB - Training Accuracy: {xgb_train_accuracy}, Validation Accuracy:
    ↪{xgb_val_accuracy}, Test Accuracy: {xgb_test_accuracy}')
```

```
XGB - Training Accuracy: 0.9752505607328339, Validation Accuracy:
0.9526880982605413, Test Accuracy: 0.953099804439565
```

[36]:
```
plot_confusion_matrix(xgb_train_cm, 'Gradient Boost Train Confusion Matrix')
plot_confusion_matrix(xgb_val_cm, 'Gradient Boost Validation Confusion Matrix')
plot_confusion_matrix(xgb_test_cm, 'Gradient Boost Test Confusion Matrix')
```




Gradient Boost Validation Confusion Matrix
15197
707
672
12571
Actual
Predicted
0
1
0
1
14000
12000
10000
8000
6000
4000
2000



[37]:

```
start_time = time.time()
# Retrieve and train best KNN models
opt_knn = gp_minimize(optimize_knn, search_space['knn'], n_calls=32,␣
  ↪random_state=42)
best_knn = cumlKNeighborsClassifier(n_neighbors=opt_knn.x[0], weights='uniform')
best_knn.fit(X_train, y_train)
y_pred_knn = best_knn.predict(X_validate)

# Print accuracy reports
print("Validation Accuracy for KNN:", accuracy_score(y_validate.values,␣
  ↪y_pred_knn))
print("Classification Report for KNN:\n", classification_report(y_validate.
  ↪values, y_pred_knn))
end_time = time.time()
total_time = end_time - start_time
print(f"Total Time: {total_time:.4f} seconds")
```

```
/home/asdf/miniconda3/envs/rapids-24.06/lib/python3.10/site-
packages/skopt/optimizer/optimizer.py:517: UserWarning: The objective has been
evaluated at point [8] before, using random point [13]
```

```
  warnings.warn(
/home/asdf/miniconda3/envs/rapids-24.06/lib/python3.10/site-
packages/skopt/optimizer/optimizer.py:517: UserWarning: The objective has been
evaluated at point [18] before, using random point [15]
  warnings.warn(
/home/asdf/miniconda3/envs/rapids-24.06/lib/python3.10/site-
packages/skopt/optimizer/optimizer.py:517: UserWarning: The objective has been
evaluated at point [15] before, using random point [12]
  warnings.warn(
/home/asdf/miniconda3/envs/rapids-24.06/lib/python3.10/site-
packages/skopt/optimizer/optimizer.py:517: UserWarning: The objective has been
evaluated at point [7] before, using random point [11]
  warnings.warn(
/home/asdf/miniconda3/envs/rapids-24.06/lib/python3.10/site-
packages/skopt/optimizer/optimizer.py:517: UserWarning: The objective has been
evaluated at point [4] before, using random point [7]
  warnings.warn(
/home/asdf/miniconda3/envs/rapids-24.06/lib/python3.10/site-
packages/skopt/optimizer/optimizer.py:517: UserWarning: The objective has been
evaluated at point [2] before, using random point [3]
  warnings.warn(
/home/asdf/miniconda3/envs/rapids-24.06/lib/python3.10/site-
packages/skopt/optimizer/optimizer.py:517: UserWarning: The objective has been
evaluated at point [13] before, using random point [8]
  warnings.warn(
/home/asdf/miniconda3/envs/rapids-24.06/lib/python3.10/site-
packages/skopt/optimizer/optimizer.py:517: UserWarning: The objective has been
evaluated at point [16] before, using random point [10]
  warnings.warn(
/home/asdf/miniconda3/envs/rapids-24.06/lib/python3.10/site-
packages/skopt/optimizer/optimizer.py:517: UserWarning: The objective has been
evaluated at point [15] before, using random point [12]
  warnings.warn(
/home/asdf/miniconda3/envs/rapids-24.06/lib/python3.10/site-
packages/skopt/optimizer/optimizer.py:517: UserWarning: The objective has been
evaluated at point [8] before, using random point [18]
  warnings.warn(

Validation Accuracy for KNN: 0.9427385322674717
Classification Report for KNN:
              precision    recall  f1-score   support

           0       0.95      0.94      0.95     15904
           1       0.93      0.94      0.94     13243

    accuracy                           0.94     29147
   macro avg       0.94      0.94      0.94     29147
weighted avg       0.94      0.94      0.94     29147
```

```
Total Time: 21.3964 seconds
```

[38]:
```
best_knn_params = dict(zip(['n_estimators', 'max_depth'], opt_knn.x))
best_knn = cumlKNeighborsClassifier(**best_knn_params, random_state=42)
best_knn.fit(X_train_gpu, y_train_gpu)
```

```
[I] [12:39:50.523350] Unused keyword parameter: n_estimators during cuML
estimator initialization
[I] [12:39:50.523434] Unused keyword parameter: random_state during cuML
estimator initialization
```

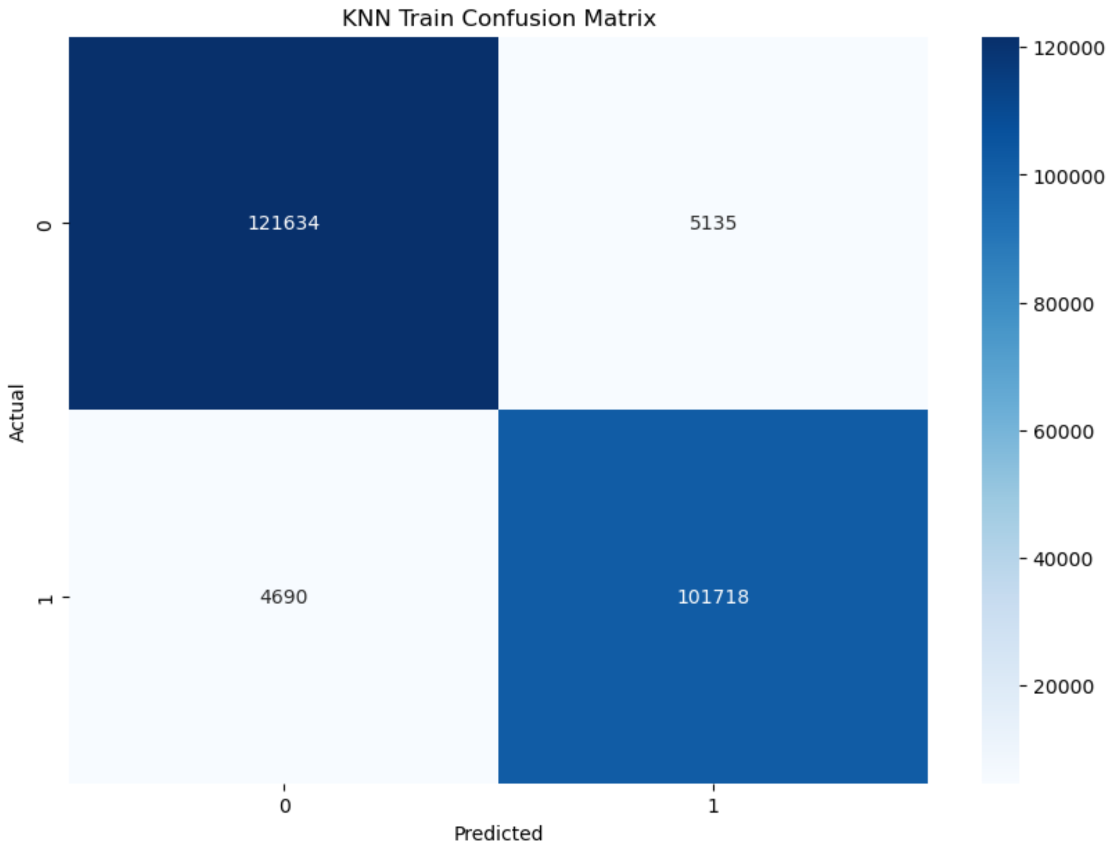
[38]:
```
KNeighborsClassifier()
```

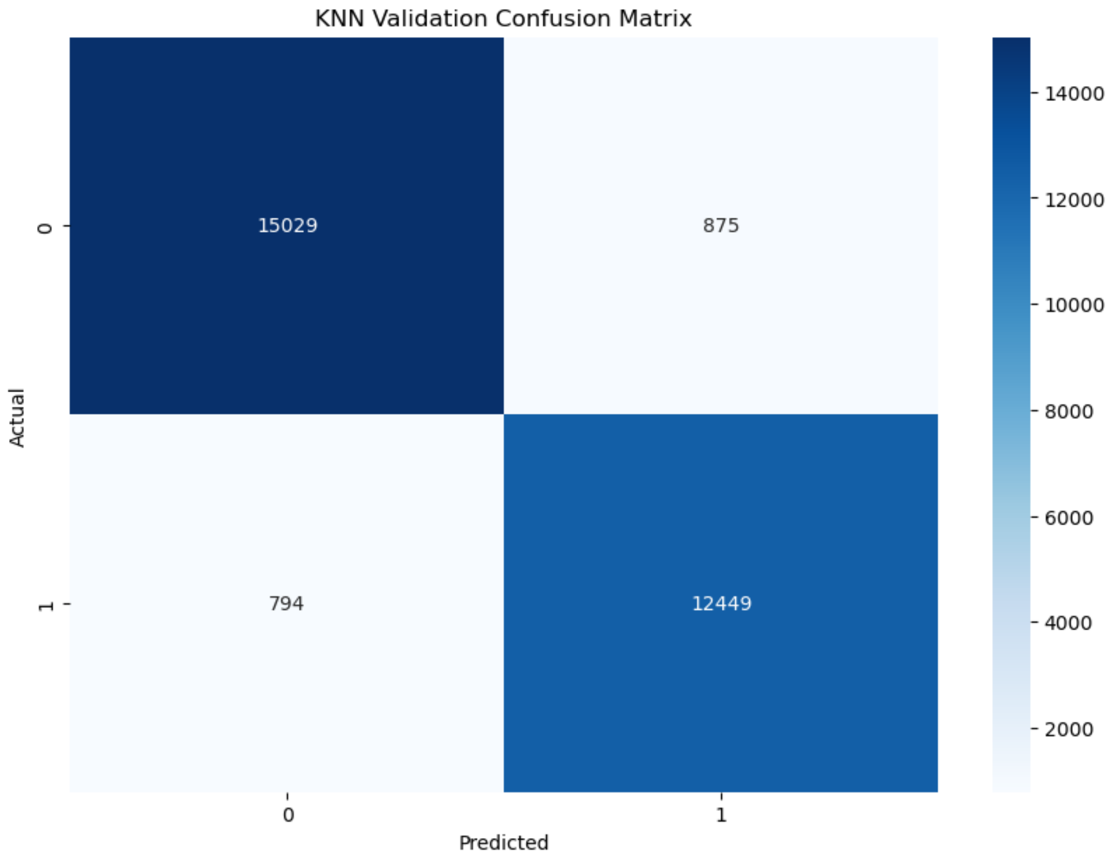
[39]:
```
knn_train_accuracy, knn_train_cm = evaluate_model(best_knn, X_train, y_train)
knn_val_accuracy, knn_val_cm = evaluate_model(best_knn, X_validate, y_validate)
knn_test_accuracy, knn_test_cm = evaluate_model(best_knn, X_test, y_test)
```

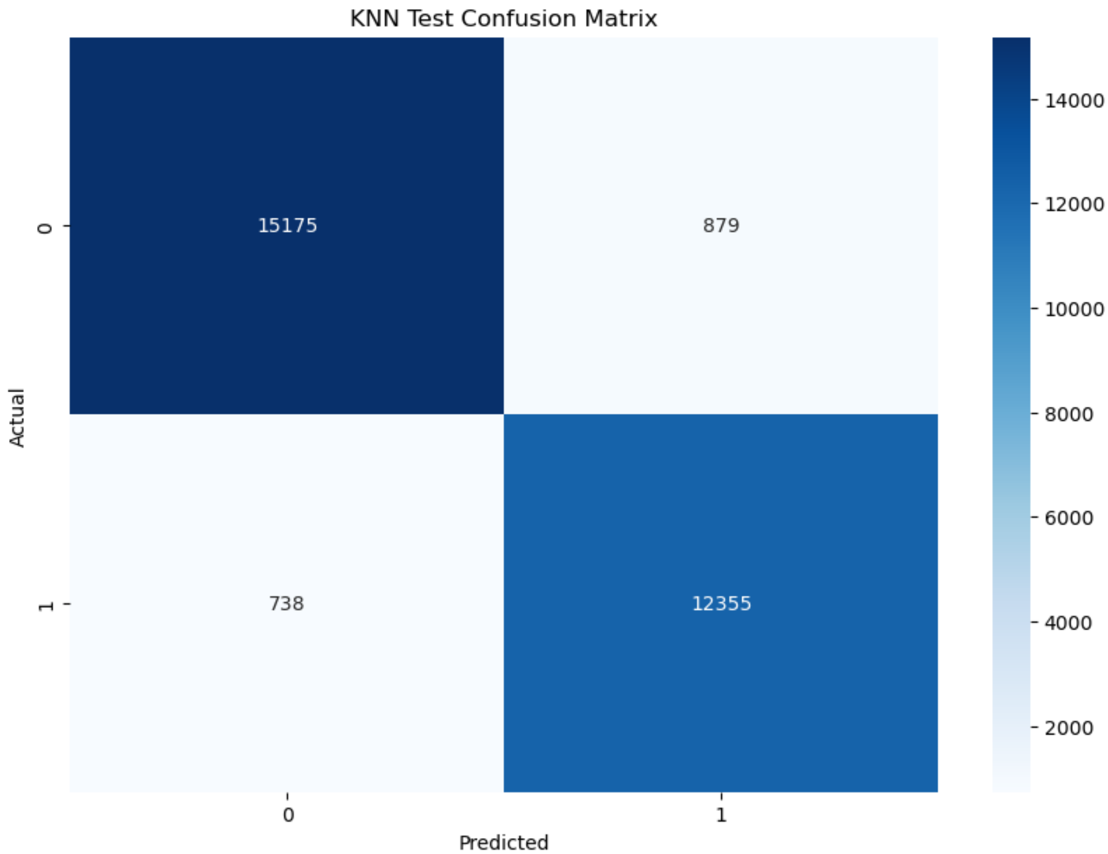
[40]:
```
print(f'KNN - Training Accuracy: {knn_train_accuracy}, Validation Accuracy:␣
↪{knn_val_accuracy}, Test Accuracy: {knn_test_accuracy}')
```

```
KNN - Training Accuracy: 0.9578646264425736, Validation Accuracy:
0.9427385322674717, Test Accuracy: 0.9445225923765739
```

[41]:
```
plot_confusion_matrix(knn_train_cm, 'KNN Train Confusion Matrix')
plot_confusion_matrix(knn_val_cm, 'KNN Validation Confusion Matrix')
plot_confusion_matrix(knn_test_cm, 'KNN Test Confusion Matrix')
```


KNN Train Confusion Matrix
Actual
0
1
121634
5135
4690
101718
Predicted
0
1
120000
100000
80000
60000
40000
20000


KNN Validation Confusion Matrix
Actual
0
1
15029
875
794
12449
Predicted
0
1
14000
12000
10000
8000
6000
4000
2000



[42]:
```
# Save the SVM model
with open('svm_model.pkl', 'wb') as file:
    pickle.dump(best_svm, file)

# Save the XGBoost model
with open('xgb_model.pkl', 'wb') as file:
    pickle.dump(best_xgb, file)

# Save the Random Forest model
with open('rf_model.pkl', 'wb') as file:
    pickle.dump(best_rf, file)

# Save the KNN model
with open('knn_model.pkl', 'wb') as file:
    pickle.dump(best_knn, file)
```

[44]:
```
import tkinter as tk
import customtkinter as ctk
import pickle
import re
```

```python
from urllib.parse import urlparse
import numpy as np

# Create the application window
app = ctk.CTk()
app.geometry("600x500")
app.title("Phishing URL Detection")

# Load the models
with open('svm_model.pkl', 'rb') as file:
    svm_model = pickle.load(file)
with open('xgb_model.pkl', 'rb') as file:
    xgb_model = pickle.load(file)
with open('rf_model.pkl', 'rb') as file:
    rf_model = pickle.load(file)
with open('knn_model.pkl', 'rb') as file:
    knn_model = pickle.load(file)

# Define the custom feature extraction functions
def count_special_chars(url):
    # Implement your logic to count special characters
    special_chars = re.findall(r'[!@#\$%\^&\*\(\)\-\+=]', url)
    return len(special_chars)

def check_url(url, words):
    # Check if URL contains a hyphen
    result = 0
    contains_hyphen = '-' in url

    # Check if URL contains any word from the list
    contains_word = any(re.search(rf'\b{word}\b', url) for word in words)

    # Return 1 if both conditions are met, else return 0
    if contains_hyphen and contains_word:
        result = 1
    else:
        result = 0
    return result

def extract_features(url):
    features = {}
    parsed_url = urlparse(url)
    domain = parsed_url.netloc

    # Extract features from the URL
    features['url_length'] = len(url)
    features['num_digits'] = sum(char.isdigit() for char in url)
```

```
    features['num_letters'] = sum(char.isalpha() for char in url)
    features['num_dots'] = url.count(".")
    features['url_depth'] = url.count("/")
    features['contains_https'] = 0 if "https" in url else 1
    features['contains_dash'] = 1 if "-" in url else 0
    features['num_subdomains'] = len(url.split('.')) - 2
    features['num_special_chars'] = count_special_chars(url)

    # Prefix and Suffix lengths
    try:
        if domain in url:
            parts = url.split(domain)
            features['prefix_length'] = len(parts[0])
            features['suffix_length'] = len(parts[1]) if len(parts) > 1 else 0
        else:
            features['prefix_length'] = 0
            features['suffix_length'] = 0
    except:
        features['prefix_length'] = 0
        features['suffix_length'] = 0

    return list(features.values())  # Return feature values as a list

# UI layout: Title
title = ctk.CTkLabel(app, text="Enter a URL to check for phishing:", 
 ↪font=("Arial", 24, "bold"))
title.pack(pady=20)

# UI layout: URL entry field
url_entry = ctk.CTkEntry(app, width=500)
url_entry.pack(pady=10)

# UI layout: Output label for overall result
output_label = ctk.CTkLabel(app, text="", font=("Arial", 18, "bold"), 
 ↪fg_color=("gray", "white"), corner_radius=8)
output_label.pack(pady=20)

# UI layout: Individual model result labels
svm_label = ctk.CTkLabel(app, text="SVM: ", font=("Arial", 18, "bold"))
svm_label.pack(pady=5)

xgb_label = ctk.CTkLabel(app, text="XGBoost: ", font=("Arial", 18, "bold"))
xgb_label.pack(pady=5)

rf_label = ctk.CTkLabel(app, text="Random Forest: ", font=("Arial", 18, "bold"))
rf_label.pack(pady=5)
```

```python
knn_label = ctk.CTkLabel(app, text="KNN: ", font=("Arial", 18, "bold"))
knn_label.pack(pady=5)

# Function to check the URL against the models
def check_url_action():
    url = url_entry.get()

    if not url:
        output_label.configure(text="Please enter a URL!", text_color="red")
        return

    # Extract features from the URL
    features = extract_features(url)
    features = np.array([features])  # Convert to 2D array for model input

    # Make predictions using the loaded models
    svm_pred = svm_model.predict(features)[0]
    xgb_pred = xgb_model.predict(features)[0]
    rf_pred = rf_model.predict(features)[0]
    knn_pred = knn_model.predict(features)[0]

    # Display the result of each model
    svm_label.configure(text=f"SVM: {'Phishing' if svm_pred == 1 else 'Safe'}", text_color=("red" if svm_pred == 1 else "green"))
    xgb_label.configure(text=f"XGBoost: {'Phishing' if xgb_pred == 1 else 'Safe'}", text_color=("red" if xgb_pred == 1 else "green"))
    rf_label.configure(text=f"Random Forest: {'Phishing' if rf_pred == 1 else 'Safe'}", text_color=("red" if rf_pred == 1 else "green"))
    knn_label.configure(text=f"KNN: {'Phishing' if knn_pred == 1 else 'Safe'}", text_color=("red" if knn_pred == 1 else "green"))

    # Collect predictions and analyze
    predictions = np.array([svm_pred, xgb_pred, rf_pred, knn_pred])
    phishing_count = np.sum(predictions)  # Count how many models predict "phishing" (1)

    # Display overall results based on majority vote
    if phishing_count >= 3:
        output_label.configure(text="This URL is likely PHISHING!", text_color="red")
    else:
        output_label.configure(text="This URL seems SAFE.", text_color="green")

# UI layout: Check button
check_button = ctk.CTkButton(app, text="Check URL", command=check_url_action, width=200)
```

```python
check_button.pack(pady=20)

# Run the application
app.mainloop()
```

```
invalid command name "139631299295296update"
    while executing
"139631299295296update"
    ("after" script)
invalid command name "139631320883456check_dpi_scaling"
    while executing
"139631320883456check_dpi_scaling"
    ("after" script)
```