

RandomForest

June 17, 2025

```
[1]: import warnings
import os
import sys
import time
import joblib
import pandas as pd
import matplotlib.pyplot as plt
import shap

from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import f1_score, precision_score, recall_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import MinMaxScaler

warnings.filterwarnings('ignore')

try:
    from data_processing import DataProcessor
    from model_evaluation import evaluate_model
except ImportError:
    if '__file__' in globals():
        script_dir = os.path.dirname(os.path.abspath(__file__))
        if os.path.basename(script_dir) == 'src':
            project_root = os.path.dirname(script_dir)
        else:
            project_root = script_dir
    else:
        current_dir = os.getcwd()
        project_root = os.path.dirname(current_dir) if current_dir.
        ↪endswith('notebooks') else current_dir

    src_dir = os.path.join(project_root, 'src')
    if src_dir not in sys.path:
        sys.path.append(src_dir)

    from data_processing import DataProcessor
    from model_evaluation import evaluate_model
```

```

if '__file__' in globals():
    script_dir = os.path.dirname(os.path.abspath(__file__))
    if os.path.basename(script_dir) == 'src':
        project_root = os.path.dirname(script_dir)
    else:
        project_root = script_dir
else:
    current_dir = os.getcwd()
    project_root = os.path.dirname(current_dir) if current_dir.
↳endswith('notebooks') else current_dir

data_dir = os.path.join(project_root, 'data')

cic_pkl_file_name = os.path.join(data_dir, "cic_dataframe.pkl")
cic_file_paths = [
    os.path.join(data_dir, f"CIC/nfstream/{day}-WorkingHours.
↳pcap_nfstream_labeled.csv")
    for day in ["Monday", "Tuesday", "Wednesday", "Thursday", "Friday"]
]

tcpdump_pkl_file_name = os.path.join(data_dir, "tcpdump_dataframe.pkl")
tcpdump_file_paths = [
    os.path.join(data_dir, f"tcpdump/nfstream/{filename}_labeled.csv")
    for filename in [
        "normal_01",
        "normal_02",
        "normal_and_attack_01",
        "normal_and_attack_02",
        "normal_and_attack_03",
        "normal_and_attack_04",
        "normal_and_attack_05",
    ]
]

# Constants
NORMAL_LABEL = 1
ANOMALY_LABEL = -1

# Configuration
test_size = 0.2
random_state = 42
scaled = False
encode_categorical = True
shap_enabled = True
dev_mode = False
corr_threshold = 0.95

```

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[2]: # 1. Load and prepare the data
print("\nStep 1: Load and prepare the data")
if os.path.exists(cic_pkl_file_name):
    print(f"Loading dataframe from {cic_pkl_file_name}")
    dataframe = pd.read_pickle(cic_pkl_file_name)
else:
    print(f"Creating dataframe from pcap files and saving to_{cic_pkl_file_name}")
    dataframe = DataProcessor.get_dataframe(file_paths=cic_file_paths)
    dataframe.to_pickle(cic_pkl_file_name)

# Add new features:
print("Adding new features to the dataframe")
dataframe = DataProcessor.add_new_features(dataframe)

# Drop object columns and handle categorical data
print("Dropping object columns except for some categorical columns")
df_without_object, available_categorical = DataProcessor.drop_object_columns(
    dataframe, encode_categorical=encode_categorical
)

# Split into features and labels
print("Splitting data into features (X) and labels (y)")
X, y = DataProcessor.split_to_X_y(df_without_object)

# Clean the data
print("Cleaning data")
DataProcessor.clean_data(X)

print(f"X.shape: {X.shape}")
print(f"y.shape: {y.shape}")

# Split the data into training and test sets
print(f"Splitting data into train and test sets with test_size={test_size}")
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=test_size, random_state=random_state, stratify=y
)

# Handle categorical encoding
print("Handling categorical encoding")
X_train, X_test, categorical_encoder = (
    DataProcessor.one_hot_encode_categorical(
        X_train, X_test, available_categorical, None
    )
)

print(f"X_train.shape: {X_train.shape}")

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print(f"X_test.shape: {X_test.shape}")

# Scaling the data
if scaled:
    print("Scaling the data")
    scaler = MinMaxScaler()
    print("New MinMaxScaler instance created")
    X_train = pd.DataFrame(
        scaler.fit_transform(X_train),
        columns=X_train.columns,
        index=X_train.index,
    )
    X_test = pd.DataFrame(
        scaler.transform(X_test),
        columns=X_test.columns,
        index=X_test.index,
    )
else:
    scaler = None

# Label conversion
print("Converting labels: benign to 1 and anomalous to -1")
y_train = y_train.map(lambda x: 1 if x == "benign" else -1)
y_test = y_test.map(lambda x: 1 if x == "benign" else -1)

# Feature selection
features_to_drop = DataProcessor.get_features_to_drop()
print(f"Always drop id, src, timestamp...: {features_to_drop}")
X_train = X_train.drop(columns=features_to_drop)
X_test = X_test.drop(columns=features_to_drop)
print(f"Dropped {len(features_to_drop)} features")

# Remove highly correlated features
print(f"Dropping highly correlated features with threshold={corr_threshold}")
X_train, dropped_corr = DataProcessor.
    ↪remove_highly_correlated_features(X_train, threshold=corr_threshold)
X_test = X_test.drop(columns=dropped_corr)
print(f"Dropped {len(dropped_corr)} features: {dropped_corr}")

print(f"X_train.shape: {X_train.shape}")
print(f"y_train.shape: {y_train.shape}")
print(f"X_test.shape: {X_test.shape}")
print(f"y_test.shape: {y_test.shape}")

# reset index to ensure consistent indexing
X_train = X_train.reset_index(drop=True)
y_train = y_train.reset_index(drop=True)

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X_test = X_test.reset_index(drop=True)
y_test = y_test.reset_index(drop=True)
```

Step 1: Load and prepare the data

Loading dataframe from /Users/seu/Library/CloudStorage/Dropbox/Docs/Study/Weiterbildung/DBS/Kurse/Projektarbeit/DS/repo/data/cic_dataframe.pkl

Adding new features to the dataframe

flow rate (bytes/sec and packets/sec)

packet rate (bytes/sec and packets/sec)

Down/Up Ratio

Dropping object columns except for some categorical columns

Retaining categorical features for encoding: ['application_name',
'application_category_name']

Number of columns before dropping object columns: 92

Dropped object columns (11): ['src_ip', 'src_mac', 'src_oui', 'dst_ip',
'dst_mac', 'dst_oui', 'requested_server_name', 'client_fingerprint',
'server_fingerprint', 'user_agent', 'content_type']

Number of columns after dropping object columns: 81

Splitting data into features (X) and labels (y)

Cleaning data

X.shape: (2916222, 80)

y.shape: (2916222,)

Splitting data into train and test sets with test_size=0.2

Handling categorical encoding

Processing categorical features: ['application_name',
'application_category_name']

Creating new OneHotEncoder

Added 261 one-hot encoded features

X_train.shape: (2332977, 339)

X_test.shape: (583245, 339)

Converting labels: benign to 1 and anomalous to -1

Always drop id, src, timestamp...: ['id', 'src_port',
'bidirectional_first_seen_ms', 'bidirectional_last_seen_ms',
'src2dst_first_seen_ms', 'src2dst_last_seen_ms', 'dst2src_first_seen_ms',
'dst2src_last_seen_ms']

Dropped 8 features

Dropping highly correlated features with threshold=0.95

Dropped 24 features: ['bidirectional_bytes', 'src2dst_duration_ms',
'src2dst_packets', 'dst2src_duration_ms', 'dst2src_packets',
'bidirectional_max_ps', 'src2dst_max_ps', 'dst2src_mean_ps',
'dst2src_stddev_ps', 'dst2src_max_ps', 'src2dst_max_piat_ms',
'bidirectional_ack_packets', 'src2dst_syn_packets', 'src2dst_cwr_packets',
'src2dst_ece_packets', 'src2dst_ack_packets', 'dst2src_ece_packets',
'dst2src_ack_packets', 'application_category_name_Download',
'application_category_name_Game', 'application_category_name_Mining',
'application_category_name_RPC', 'application_category_name_Shopping',
'application_category_name_Unspecified']

```
X_train.shape: (2332977, 307)
y_train.shape: (2332977,)
X_test.shape: (583245, 307)
y_test.shape: (583245,)
```

```
[3]: # 2. Feature Selection
print("\nStep 2: Feature Selection using Random Forest Classifier")

rfc_selector = RandomForestClassifier(
    n_estimators=100,
    max_depth=10,
    min_samples_split=5,
    min_samples_leaf=2,
    max_features='sqrt',
    random_state=random_state,
    n_jobs=-1
)

rfc_selector.fit(X_train, y_train)

# Feature Importance Extraction
feature_importance = rfc_selector.feature_importances_
feature_names = X_train.columns
# sort features by importance
importance_df = pd.DataFrame({
    'feature': feature_names,
    'importance': feature_importance
}).sort_values('importance', ascending=False)

print(f"Total features: {len(feature_names)}")
print(f"Random Forest with {rfc_selector.n_estimators} trees trained")
print("\nTop 20 most important features:")
print(importance_df.head(20))

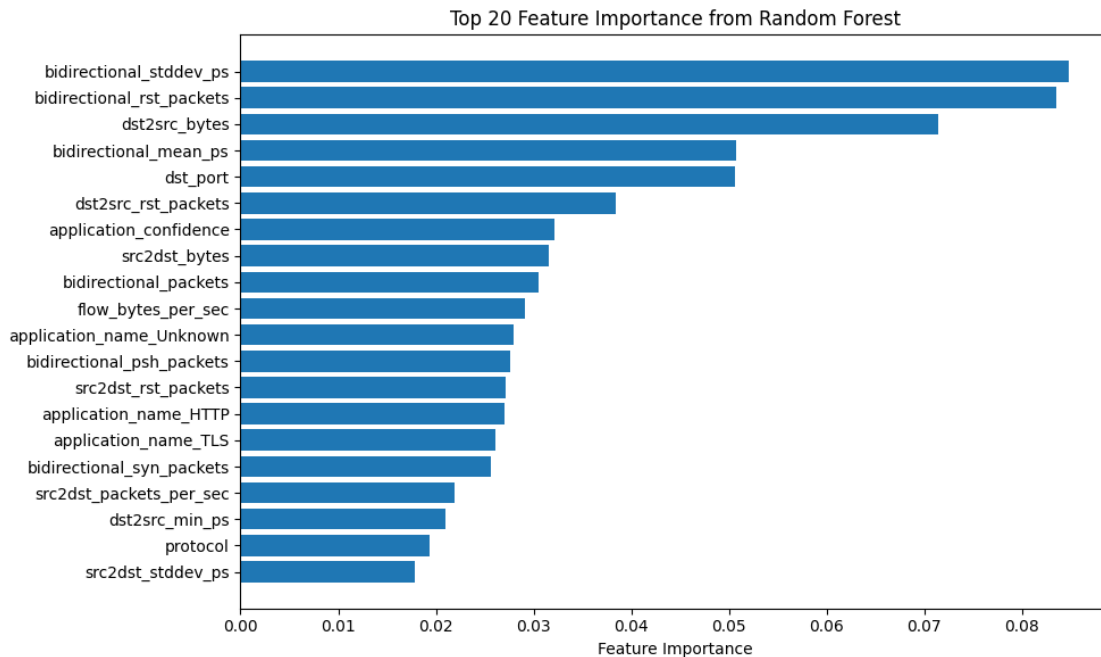
# visualize feature importance
plt.figure(figsize=(10, 6))
top_features = importance_df.head(20)
plt.barh(range(len(top_features)), top_features['importance'])
plt.yticks(range(len(top_features)), top_features['feature'])
plt.xlabel('Feature Importance')
plt.title('Top 20 Feature Importance from Random Forest')
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show(block=False)
```

Step 2: Feature Selection using Random Forest Classifier
Total features: 307

Random Forest with 100 trees trained

Top 20 most important features:

	feature	importance
12	bidirectional_stddev_ps	0.084748
33	bidirectional_rst_packets	0.083522
9	dst2src_bytes	0.071479
11	bidirectional_mean_ps	0.050756
1	dst_port	0.050579
43	dst2src_rst_packets	0.038378
46	application_confidence	0.032124
8	src2dst_bytes	0.031562
7	bidirectional_packets	0.030574
47	flow_bytes_per_sec	0.029129
281	application_name_Unknown	0.027939
32	bidirectional_psh_packets	0.027555
37	src2dst_rst_packets	0.027199
137	application_name_HTTP	0.027083
217	application_name_TLS	0.026072
28	bidirectional_syn_packets	0.025665
49	src2dst_packets_per_sec	0.021941
16	dst2src_min_ps	0.020947
2	protocol	0.019319
15	src2dst_stddev_ps	0.017827



```

[4]: # 3. Compare number of features and cumulative importance
print("\nStep 3: Compare number of features and cumulative importance")
target_features_list = [1, 10, 25, 50, 75, 100, 125, 150, 175, 200]
results_comparison = []

for n_features in target_features_list:
    # select top n_features based on importance
    top_features_df = importance_df.head(n_features)
    top_features_list = top_features_df['feature'].tolist()

    X_train_split, X_val_split, y_train_split, y_val_split = train_test_split(
        X_train, y_train,
        test_size=test_size,
        random_state=random_state,
        stratify=y_train
    )

    X_train_split_selected = X_train_split[top_features_list]
    X_val_split_selected = X_val_split[top_features_list]

    # print(f"X_train_split_selected.shape: {X_train_split_selected.shape}")
    # print(f"X_val_split_selected.shape: {X_val_split_selected.shape}")

    # Validate model for selected features
    test_rf = RandomForestClassifier(
        n_estimators=20,
        max_depth=5,
        min_samples_split=5,
        min_samples_leaf=2,
        max_features='sqrt',
        random_state=random_state,
    )

    test_rf.fit(X_train_split_selected, y_train_split)
    y_pred = test_rf.predict(X_val_split_selected)

    # metrics calculation
    accuracy = test_rf.score(X_val_split_selected, y_val_split)
    f1 = f1_score(y_val_split, y_pred, average='weighted') # weighted average
    ↪for unbalanced classes
    precision = precision_score(y_val_split, y_pred, average='weighted')
    recall = recall_score(y_val_split, y_pred, average='weighted')
    print(f"Features: {n_features:2d}, F1(weighted): {f1:.4f}, "
          f"Accuracy: {accuracy:.4f}, Precision: {precision:.4f}, Recall:
    ↪{recall:.4f}")

    # cumulative importance of selected features

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cumulative_importance = top_features_df['importance'].sum()

results_comparison.append({
    'n_features': n_features,
    'accuracy': accuracy,
    'f1_weighted': f1,
    'precision': precision,
    'recall': recall,
    'cumulative_importance': cumulative_importance
})

# visualize results
results_df = pd.DataFrame(results_comparison)
fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2, figsize=(15, 12))

# n_features vs F1 Score
ax1.plot(results_df['n_features'], results_df['f1_weighted'], 'bo-', label='F1_Weighted')
ax1.set_xlabel('Number of Features')
ax1.set_ylabel('F1 Score')
ax1.set_title('F1 Score vs Number of Features')
ax1.legend()
ax1.grid(True, alpha=0.3)

# n_features vs Precision/Recall
ax2.plot(results_df['n_features'], results_df['precision'], 'go-', label='Precision')
ax2.plot(results_df['n_features'], results_df['recall'], 'mx-', label='Recall')
ax2.set_xlabel('Number of Features')
ax2.set_ylabel('Score')
ax2.set_title('Precision/Recall vs Number of Features')
ax2.legend()
ax2.grid(True, alpha=0.3)

# n_features vs Cumulative Feature Importance
ax3.plot(results_df['n_features'], results_df['cumulative_importance'], 'co-', label='Cumulative Importance')
ax3.set_xlabel('Number of Features')
ax3.set_ylabel('Cumulative Feature Importance')
ax3.set_title('Feature Importance Coverage')
ax3.grid(True, alpha=0.3)

# f1 Score vs Accuracy Comparison
ax4.plot(results_df['n_features'], results_df['accuracy'], 'ko-', label='Accuracy')
ax4.plot(results_df['n_features'], results_df['f1_weighted'], 'bx-', label='F1_Weighted')

```

```

ax4.set_xlabel('Number of Features')
ax4.set_ylabel('Score')
ax4.set_title('Accuracy vs F1 Score Comparison')
ax4.legend()
ax4.grid(True, alpha=0.3)

plt.tight_layout()
plt.show(block=False)

# result summary
print("\n=== Feature Selection Results Summary (All Metrics) ===")
print(results_df.round(4))

# optimal feature selection based on F1 score
best_f1_idx = results_df['f1_weighted'].idxmax()
best_f1_result = results_df.iloc[best_f1_idx]

print("\n=== Optimal Feature Selection Results ===")
print(f"Best F1 (weighted): {best_f1_result['f1_weighted']:.4f} with {best_f1_result['n_features']} features")
print(f" - Accuracy: {best_f1_result['accuracy']:.4f}")
print(f" - Precision: {best_f1_result['precision']:.4f}")
print(f" - Recall: {best_f1_result['recall']:.4f}")
print(f" - Feature importance coverage: {best_f1_result['cumulative_importance']:.3f}")

print("\nOptimal Feature Selection based on F1 Score")
print("=== optimal features ===")
optimal_f1_features = int(best_f1_result['n_features'])
optimal_features_list = importance_df.head(optimal_f1_features)['feature'].tolist()

X_train_optimal = X_train[optimal_features_list]
X_test_optimal = X_test[optimal_features_list]

print(f"optimal_features_list = {optimal_features_list}")
print(f"X_train_optimal.shape: {X_train_optimal.shape}")

```

Step 3: Compare number of features and cumulative importance

Features: 1, F1(weighted): 0.9467, Accuracy: 0.9500, Precision: 0.9509, Recall: 0.9500

Features: 10, F1(weighted): 0.9876, Accuracy: 0.9877, Precision: 0.9877, Recall: 0.9877

Features: 25, F1(weighted): 0.9908, Accuracy: 0.9908, Precision: 0.9908, Recall: 0.9908

Features: 50, F1(weighted): 0.9894, Accuracy: 0.9894, Precision: 0.9894, Recall:

0.9894

Features: 75, F1(weighted): 0.9892, Accuracy: 0.9892, Precision: 0.9892, Recall: 0.9892

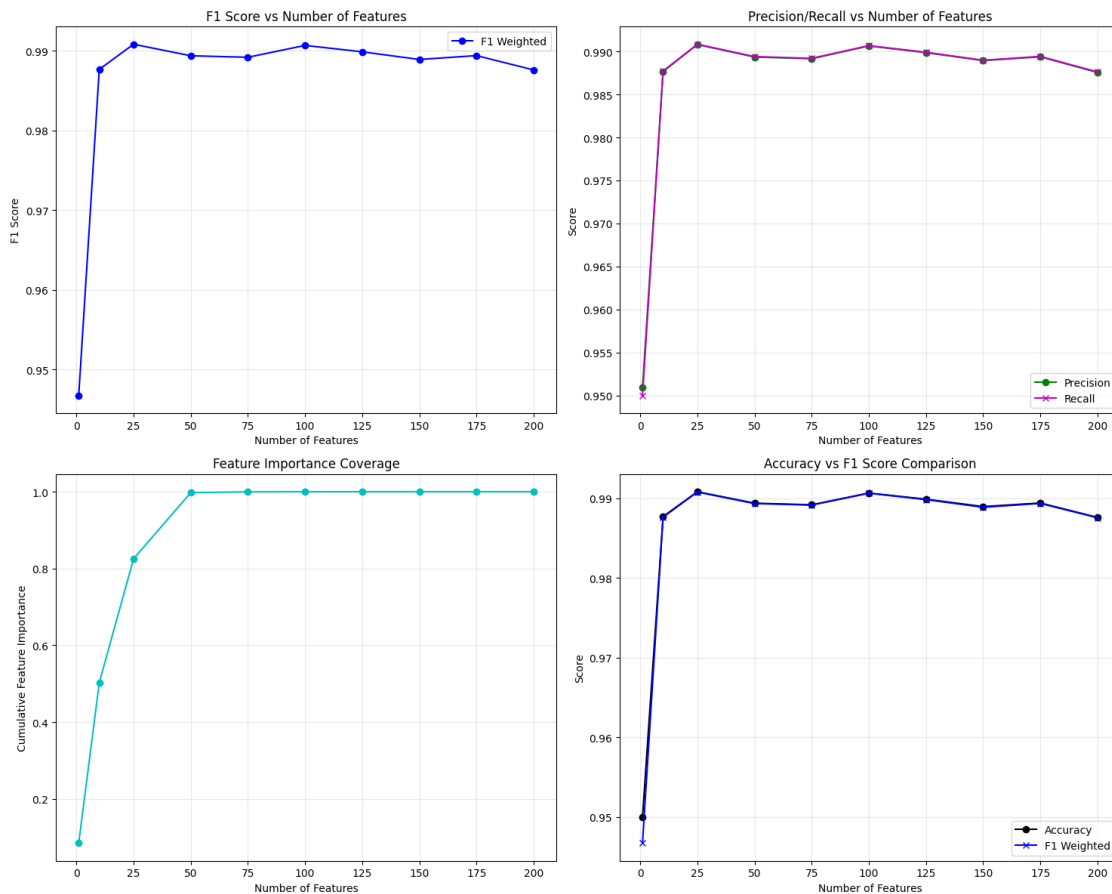
Features: 100, F1(weighted): 0.9906, Accuracy: 0.9907, Precision: 0.9906, Recall: 0.9907

Features: 125, F1(weighted): 0.9898, Accuracy: 0.9899, Precision: 0.9899, Recall: 0.9899

Features: 150, F1(weighted): 0.9889, Accuracy: 0.9890, Precision: 0.9889, Recall: 0.9890

Features: 175, F1(weighted): 0.9894, Accuracy: 0.9894, Precision: 0.9894, Recall: 0.9894

Features: 200, F1(weighted): 0.9876, Accuracy: 0.9876, Precision: 0.9876, Recall: 0.9876



=== Feature Selection Results Summary (All Metrics) ===

	n_features	accuracy	f1_weighted	precision	recall	cumulative_importance
0	1	0.9500	0.9467	0.9509	0.9500	0.0847
1	10	0.9877	0.9876	0.9877	0.9877	0.5029
2	25	0.9908	0.9908	0.9908	0.9908	0.8254

3	50	0.9894	0.9894	0.9894	0.9894	0.9975
4	75	0.9892	0.9892	0.9892	0.9892	0.9998
5	100	0.9907	0.9906	0.9906	0.9907	1.0000
6	125	0.9899	0.9898	0.9899	0.9899	1.0000
7	150	0.9890	0.9889	0.9889	0.9890	1.0000
8	175	0.9894	0.9894	0.9894	0.9894	1.0000
9	200	0.9876	0.9876	0.9876	0.9876	1.0000

=== Optimal Feature Selection Results ===

Best F1 (weighted): 0.9908 with 25.0 features

- Accuracy: 0.9908
- Precision: 0.9908
- Recall: 0.9908
- Feature importance coverage: 0.825

Optimal Feature Selection based on F1 Score

=== optimal features ===

```
optimal_features_list = ['bidirectional_stddev_ps', 'bidirectional_rst_packets',
'dst2src_bytes', 'bidirectional_mean_ps', 'dst_port', 'dst2src_rst_packets',
'application_confidence', 'src2dst_bytes', 'bidirectional_packets',
'flow_bytes_per_sec', 'application_name_Unknown', 'bidirectional_psh_packets',
'src2dst_rst_packets', 'application_name_HTTP', 'application_name_TLS',
'bidirectional_syn_packets', 'src2dst_packets_per_sec', 'dst2src_min_ps',
'protocol', 'src2dst_stddev_ps', 'src2dst_mean_ps', 'flow_packets_psr_sec',
'bidirectional_fin_packets', 'dst2src_ackets_per_sec', 'src2dst_psh_packets']
```

X_train_optimal.shape: (2332977, 25)

```
[5]: # 4. Hyperparameter tuning
print("\nStep 4: Hyperparameter Tuning using Grid Search")

def tune_hyperparameters(X_train, y_train, dev_mode=False):
    if dev_mode:
        param_grid = {
            'n_estimators': [100],
            'max_depth': [10],
            'min_samples_split': [5],
            'min_samples_leaf': [2],
            'max_features': ['sqrt'],
            'random_state': [random_state]
        }
        cv = 2
    else:
        param_grid = {
            'n_estimators': [50, 100],
            'max_depth': [5, 7, 10],
            'min_samples_split': [2, 5],
            'min_samples_leaf': [1, 2],
```

```

        'max_features': ['sqrt', 'log2'],
        'random_state': [random_state]
    }
    cv = 3

    rf_tuner = RandomForestClassifier()
    grid_search = GridSearchCV(
        rf_tuner,
        param_grid,
        scoring='f1_weighted',
        cv=cv,
        verbose=2,
        n_jobs=-1
    )

    total_combinations = 1
    for param_values in param_grid.values():
        total_combinations *= len(param_values)

    print(f"Testing {total_combinations} parameter combinations...")
    start_time = time.time()

    grid_search.fit(X_train, y_train)

    end_time = time.time()
    print(f"Grid search completed in {end_time - start_time:.2f} seconds")
    print(f"Best parameters: {grid_search.best_params_}")
    print(f"Best CV score: {grid_search.best_score_:.4f}")

    return grid_search.best_estimator_

# Hyperparameter tuning
best_rf_model = tune_hyperparameters(X_train_optimal, y_train,
    ↪dev_mode=dev_mode)

```

Step 4: Hyperparameter Tuning using Grid Search

Testing 48 parameter combinations...

Fitting 3 folds for each of 48 candidates, totalling 144 fits

```

[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=2,
min_samples_split=2, n_estimators=50, random_state=42; total time= 47.2s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=1,
min_samples_split=2, n_estimators=50, random_state=42; total time= 47.3s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=1,
min_samples_split=5, n_estimators=50, random_state=42; total time= 47.5s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=1,
min_samples_split=2, n_estimators=50, random_state=42; total time= 47.5s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=1,

```

[illegible]

[illegible]

[illegible]

```

min_samples_split=5, n_estimators=100, random_state=42; total time= 2.5min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=2,
min_samples_split=2, n_estimators=50, random_state=42; total time= 55.9s
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.5min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.8min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=1,
min_samples_split=2, n_estimators=100, random_state=42; total time= 2.0min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=1,
min_samples_split=5, n_estimators=100, random_state=42; total time= 1.9min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=1,
min_samples_split=2, n_estimators=100, random_state=42; total time= 2.4min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=2,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.2min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=1,
min_samples_split=2, n_estimators=100, random_state=42; total time= 2.4min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=2,
min_samples_split=5, n_estimators=50, random_state=42; total time= 58.6s
[CV] END max_depth=10, max_features=log2, min_samples_leaf=2,
min_samples_split=5, n_estimators=50, random_state=42; total time= 59.6s
[CV] END max_depth=10, max_features=log2, min_samples_leaf=2,
min_samples_split=5, n_estimators=50, random_state=42; total time= 1.1min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=1,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.3min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=1,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.4min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=2,
min_samples_split=2, n_estimators=100, random_state=42; total time= 1.8min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=2,
min_samples_split=2, n_estimators=100, random_state=42; total time= 1.8min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=2,
min_samples_split=2, n_estimators=100, random_state=42; total time= 1.9min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 1.7min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 1.6min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 1.6min
Grid search completed in 1058.37 seconds
Best parameters: {'max_depth': 10, 'max_features': 'log2', 'min_samples_leaf':
1, 'min_samples_split': 2, 'n_estimators': 100, 'random_state': 42}
Best CV score: 0.9965

```

```

[6]: # 5. Final Random Forest Classifier model training and evaluation
print("\nStep 5: Final Random Forest Classifier model training and evaluation")
max_depth = best_rf_model.get_params()['max_depth']

```

```

max_features = best_rf_model.get_params()['max_features']
min_samples_leaf = best_rf_model.get_params()['min_samples_leaf']
min_samples_split = best_rf_model.get_params()['min_samples_split']
n_estimators = best_rf_model.get_params()['n_estimators']
random_state = best_rf_model.get_params()['random_state']
print(f"Best Random Forest model with parameters: n_estimators={n_estimators}, "
      f"max_depth={max_depth}, min_samples_split={min_samples_split}, "
      f"min_samples_leaf={min_samples_leaf}, max_features={max_features}, "
      f"random_state={random_state}")

rf = RandomForestClassifier(
    n_estimators=n_estimators,
    max_depth=max_depth,
    min_samples_split=min_samples_split,
    min_samples_leaf=min_samples_leaf,
    max_features=max_features,
    random_state=random_state
)
# Train the model
print("Training the Random Forest model with optimal features...")
rf.fit(X_train_optimal, y_train)
print("Model trained successfully.")

evaluate_model(rf, X_test_optimal, y_test)

```

Step 5: Final Random Forest Classifier model training and evaluation
 Best Random Forest model with parameters: n_estimators=100, max_depth=10,
 min_samples_split=2, min_samples_leaf=1, max_features=log2, random_state=42
 Training the Random Forest model with optimal features...
 Model trained successfully.
 using predict_proba for prediction scores

Test Data - BENIGN Count: 489792, Ratio: 83.98%
 Test Data - ANOMALOUS Count: 93453, Ratio: 16.02%

Test result:

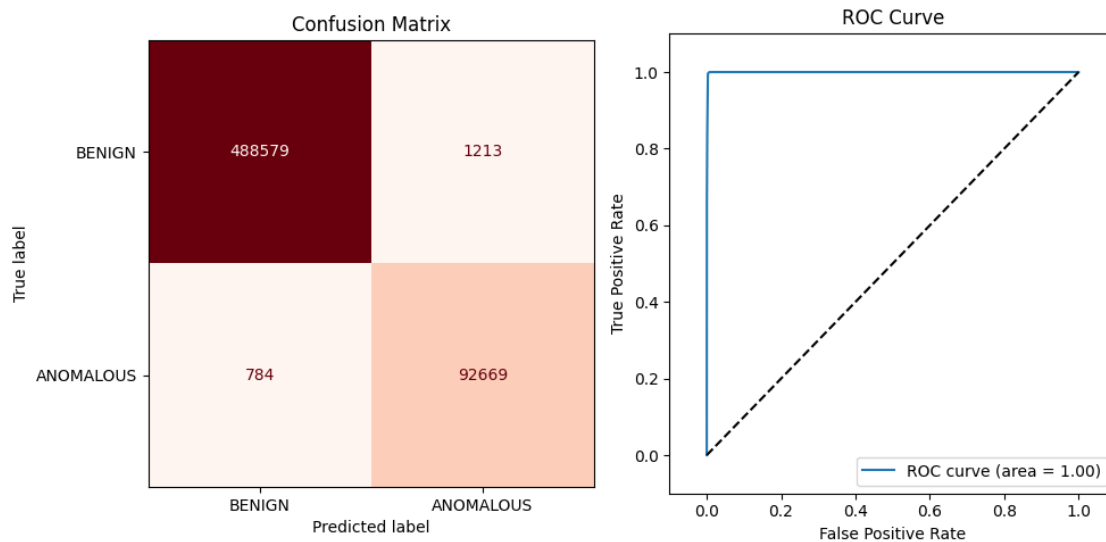
	precision	recall	f1-score	support
BENIGN	1.00	1.00	1.00	489792
ANOMALOUS	0.99	0.99	0.99	93453
accuracy			1.00	583245
macro avg	0.99	0.99	0.99	583245
weighted avg	1.00	1.00	1.00	583245

```

[[488579 1213]
 [ 784 92669]]

```

Precision: 0.987
Recall: 0.992
False Positive Rate: 0.002
False Negative Rate: 0.008
F1-Score: 0.989
Area under the curve: 1.000



```
[7]: # 6. Evaluate with tcpdump data
print("\nStep 6: Evaluate with tcpdump data")
if os.path.exists(tcpdump_pkl_file_name):
    print(f"Loading dataframe from {tcpdump_pkl_file_name}")
    tcpdump_dataframe = pd.read_pickle(tcpdump_pkl_file_name)
else:
    print(f"Creating dataframe from pcap files and saving to {tcpdump_pkl_file_name}")
    tcpdump_dataframe = DataProcessor.get_dataframe(file_paths=tcpdump_file_paths)
    tcpdump_dataframe.to_pickle(tcpdump_pkl_file_name)

# Add new features:
print("Adding new features to the dataframe...")
tcpdump_dataframe = DataProcessor.add_new_features(tcpdump_dataframe)

# Drop object columns and handle categorical data
print("Dropping object columns and handle encoding categorical data...")
tcpdump_df_without_object, available_categorical = DataProcessor.drop_object_columns(
    tcpdump_dataframe, encode_categorical=encode_categorical
```

```

    )
    # Split into features and labels
    print("Splitting data into features (X) and labels (y)...")
    X_tcpdump, y_tcpdump = DataProcessor.split_to_X_y(tcpdump_df_without_object)

    print("Cleaning data...")
    DataProcessor.clean_data(X_tcpdump)

    print(f"X_tcpdump.shape: {X_tcpdump.shape}")
    print(f"y_tcpdump.shape: {y_tcpdump.shape}")

    print("Handling categorical encoding...")
    print(f"Available categorical features: {available_categorical}")
    print(f"Use categorical_encoder: {categorical_encoder}")
    X_tcpdump, _, categorical_encoder = (
        DataProcessor.one_hot_encode_categorical(
            X_tcpdump, None, available_categorical, categorical_encoder
        )
    )
    print(f"X_tcpdump.shape: {X_tcpdump.shape}")

    if scaled and scaler is not None:
        print(f"Use MinMaxScaler instance: {scaler}")
        X_tcpdump = pd.DataFrame(
            scaler.transform(X_tcpdump),
            columns=X_tcpdump.columns,
            index=X_tcpdump.index,
        )

    y_tcpdump = y_tcpdump.map(lambda x: 1 if x == "benign" else -1)

    # Feature selection
    print("Feature selection:")
    X_tcpdump_optimal = X_tcpdump[optimal_features_list]

    print(f"X_tcpdump_optimal.shape: {X_tcpdump_optimal.shape}")
    print(f"y_tcpdump.shape: {y_tcpdump.shape}")

    evaluate_model(rf, X_tcpdump_optimal, y_tcpdump, with_numpy=True)

```

Step 6: Evaluate with tcpdump data

Loading dataframe from /Users/seu/Library/CloudStorage/Dropbox/Docs/Study/Weiterbildung/DBS/Kurse/Projektarbeit/DS/repo/data/tcpdump_dataframe.pkl

Adding new features to the dataframe...

flow rate (bytes/sec and packets/sec)

packet rate (bytes/sec and packets/sec)

Down/Up Ratio

Dropping object columns and handle encoding categorical data...
 Retaining categorical features for encoding: ['application_name',
 'application_category_name']
 Number of columns before dropping object columns: 92
 Dropped object columns (11): ['src_ip', 'src_mac', 'src_oui', 'dst_ip',
 'dst_mac', 'dst_oui', 'requested_server_name', 'client_fingerprint',
 'server_fingerprint', 'user_agent', 'content_type']
 Number of columns after dropping object columns: 81
 Splitting data into features (X) and labels (y)...
 Cleaning data...
 X_tcpdump.shape: (73180, 80)
 y_tcpdump.shape: (73180,)
 Handling categorical encoding...
 Available categorical features: ['application_name',
 'application_category_name']
 Use categorical_encoder: OneHotEncoder(drop='first', handle_unknown='ignore',
 sparse_output=False)
 Processing categorical features: ['application_name',
 'application_category_name']
 Using existing OneHotEncoder
 Added 261 one-hot encoded features
 X_tcpdump.shape: (73180, 339)
 Feature selection:
 X_tcpdump_optimal.shape: (73180, 25)
 y_tcpdump.shape: (73180,)
 using predict_proba for prediction scores

Test Data - BENIGN Count: 46070, Ratio: 62.95%
 Test Data - ANOMALOUS Count: 27110, Ratio: 37.05%

Test result:

	precision	recall	f1-score	support
BENIGN	0.64	0.17	0.27	46070
ANOMALOUS	0.37	0.84	0.52	27110
accuracy			0.42	73180
macro avg	0.51	0.50	0.39	73180
weighted avg	0.54	0.42	0.36	73180

[[7879 38191]
 [4383 22727]]

Precision: 0.373

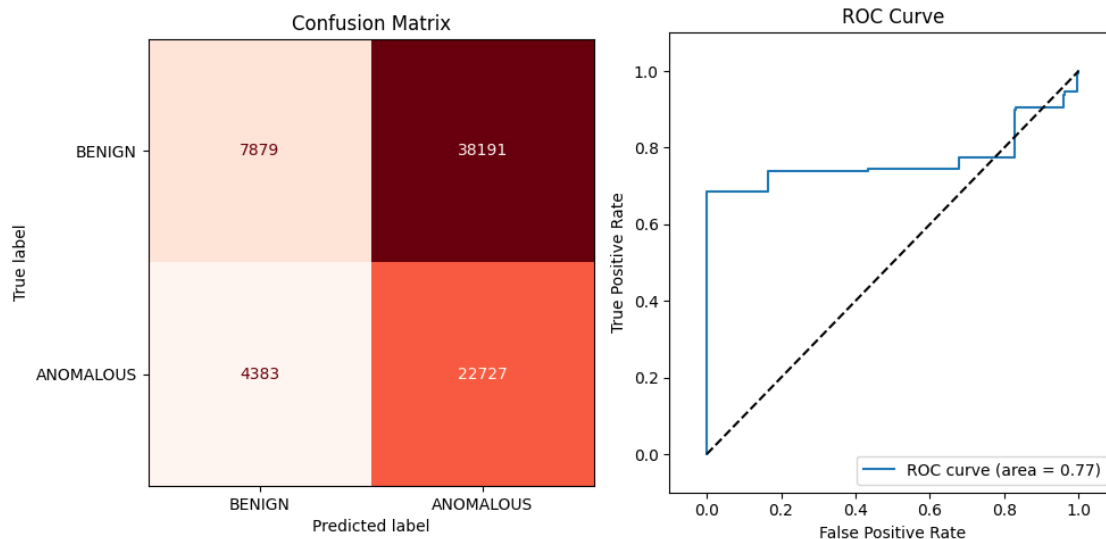
Recall: 0.838

False Positive Rate: 0.829

False Negative Rate: 0.162

F1-Score: 0.516

Area under the curve: 0.768



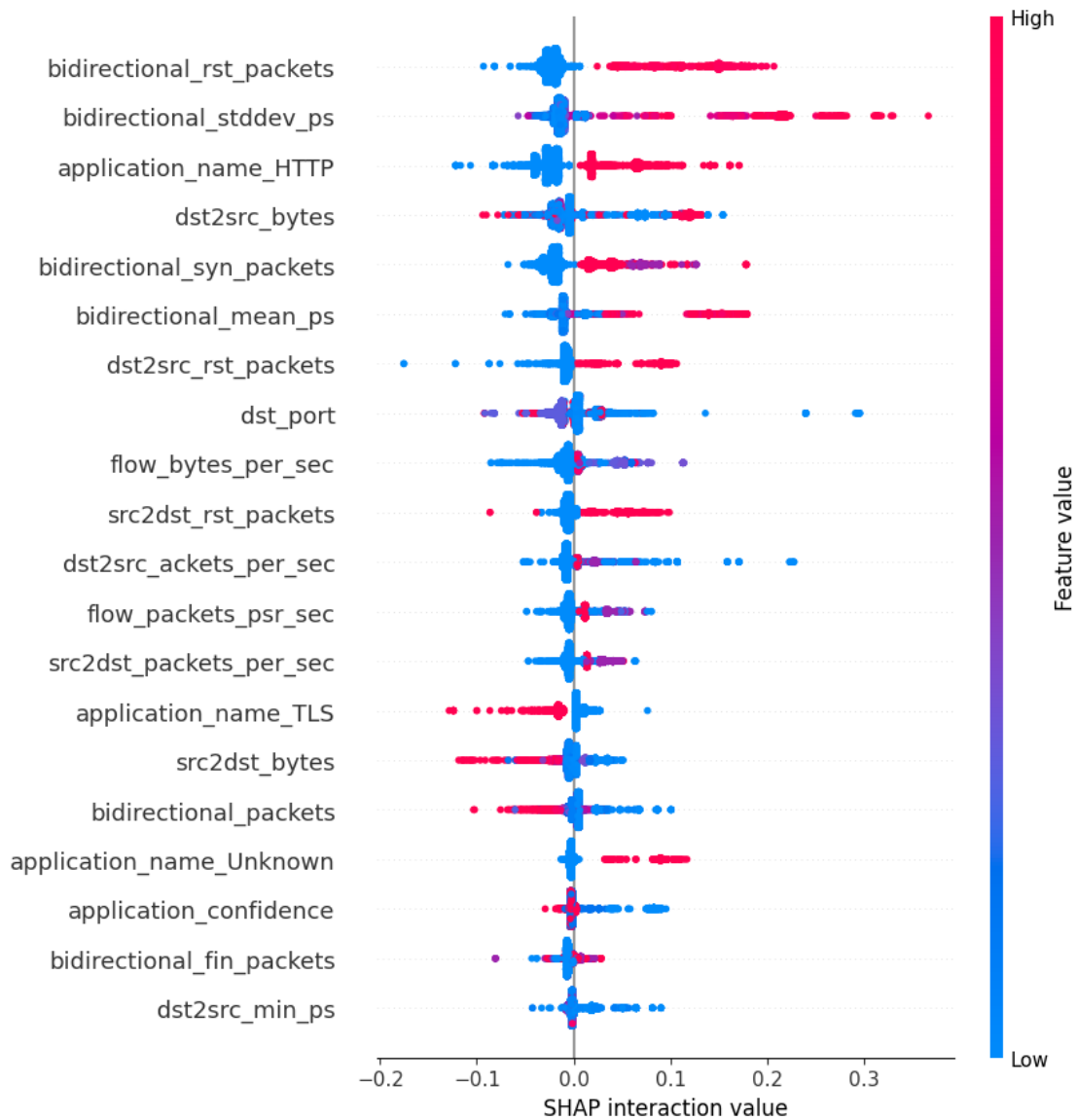
```
[8]: # 7. Interpretation with SHAP
shap_enabled = True
if shap_enabled:
    print("\nStep 7: Interpretation with SHAP")
    explainer = shap.TreeExplainer(rf)
    X_test_optimal_sampled = X_test_optimal.sample(n=10000,
    ↪random_state=random_state)
    shap_values = explainer.shap_values(X_test_optimal_sampled)

    plt.figure(figsize=(14, 8))

    if len(shap_values.shape) == 3:
        main_effects = shap_values[:, :, :-1].sum(axis=2)
        shap.summary_plot(main_effects, X_test_optimal_sampled,
    ↪feature_names=optimal_features_list, show=False)
    else:
        shap.summary_plot(shap_values, X_test_optimal_sampled,
    ↪feature_names=optimal_features_list, show=False)

    plt.tight_layout()
    plt.subplots_adjust(left=0.15, right=0.85, top=0.95, bottom=0.1)
    plt.xlabel('SHAP interaction value', fontsize=12)
    plt.show()
```

Step 7: Interpretation with SHAP



```
[9]: # 8. Feature Importance
print("\nStep 8: Feature Importance")
with pd.option_context('display.max_rows', None):
    print(importance_df.head(len(optimal_features_list)))
```

Step 8: Feature Importance

	feature	importance
12	bidirectional_stddev_ps	0.084748
33	bidirectional_rst_packets	0.083522
9	dst2src_bytes	0.071479
11	bidirectional_mean_ps	0.050756

1	dst_port	0.050579
43	dst2src_rst_packets	0.038378
46	application_confidence	0.032124
8	src2dst_bytes	0.031562
7	bidirectional_packets	0.030574
47	flow_bytes_per_sec	0.029129
281	application_name_Unknown	0.027939
32	bidirectional_psh_packets	0.027555
37	src2dst_rst_packets	0.027199
137	application_name_HTTP	0.027083
217	application_name_TLS	0.026072
28	bidirectional_syn_packets	0.025665
49	src2dst_packets_per_sec	0.021941
16	dst2src_min_ps	0.020947
2	protocol	0.019319
15	src2dst_stddev_ps	0.017827
14	src2dst_mean_ps	0.016880
48	flow_packets_psr_sec	0.016514
34	bidirectional_fin_packets	0.016263
50	dst2src_ackets_per_sec	0.016198
36	src2dst_psh_packets	0.015190

```
[10]: model_dir = os.path.join(project_root, 'models', 'rf')
if not os.path.exists(model_dir):
    os.makedirs(model_dir)
    print(f"Created model directory: {model_dir}")

# save the model
model_file_name = os.path.join(model_dir, "model.pkl")
print(f"Saving the model to {model_file_name}")
joblib.dump(rf, model_file_name)
print("Model saved successfully.")

# save the encoder
encoder_file_name = os.path.join(model_dir, "encoder.pkl")
print(f"Saving the encoder to {encoder_file_name}")
joblib.dump(categorical_encoder, encoder_file_name)
print("Encoder saved successfully.")

# save the importance_df
importance_file_name = os.path.join(model_dir, "importance_df.pkl")
print(f"Saving the importance DataFrame to {importance_file_name}")
importance_df.to_pickle(importance_file_name)
print("Importance DataFrame saved successfully.")

# save the optimal_features_list
```

```
optimal_features_file_name = os.path.join(model_dir, "optimal_features_list.  
    ↪pkl")  
print(f"Saving the optimal features list to {optimal_features_file_name}")  
joblib.dump(optimal_features_list, optimal_features_file_name)  
print("Optimal features list saved successfully.")
```

Created model directory: /Users/seu/Library/CloudStorage/Dropbox/Docs/Study/Weiterbildung/DBS/Kurse/Projektarbeit/DS/repo/models/rf
Saving the model to /Users/seu/Library/CloudStorage/Dropbox/Docs/Study/Weiterbildung/DBS/Kurse/Projektarbeit/DS/repo/models/rf/model.pkl
Model saved successfully.
Saving the encoder to /Users/seu/Library/CloudStorage/Dropbox/Docs/Study/Weiterbildung/DBS/Kurse/Projektarbeit/DS/repo/models/rf/encoder.pkl
Encoder saved successfully.
Saving the importance DataFrame to /Users/seu/Library/CloudStorage/Dropbox/Docs/Study/Weiterbildung/DBS/Kurse/Projektarbeit/DS/repo/models/rf/importance_df.pkl
Importance DataFrame saved successfully.
Saving the optimal features list to /Users/seu/Library/CloudStorage/Dropbox/Docs/Study/Weiterbildung/DBS/Kurse/Projektarbeit/DS/repo/models/rf/optimal_features_list.pkl
Optimal features list saved successfully.