RandomForest

June 19, 2025

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

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

[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 {os.path.basename(cic_pkl_file_name)}")
    dataframe = pd.read_pickle(cic_pkl_file_name)
else:
    print(f"Creating dataframe from pcap files and saving to {os.path.
 ↪basename(cic_pkl_file_name)}")
    dataframe = DataProcessor.get_dataframe(file_paths=cic_file_paths)
    dataframe.to_pickle(cic_pkl_file_name)

# Add new featueres:
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
    )
)
```

```python
print(f"X_train.shape: {X_train.shape}")
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"Droped {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"Droped {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
```

```python
X_train = X_train.reset_index(drop=True)
y_train = y_train.reset_index(drop=True)
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 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']
Droped 8 features
Dropping highly correlated features with threshold=0.95
Droped 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',
```

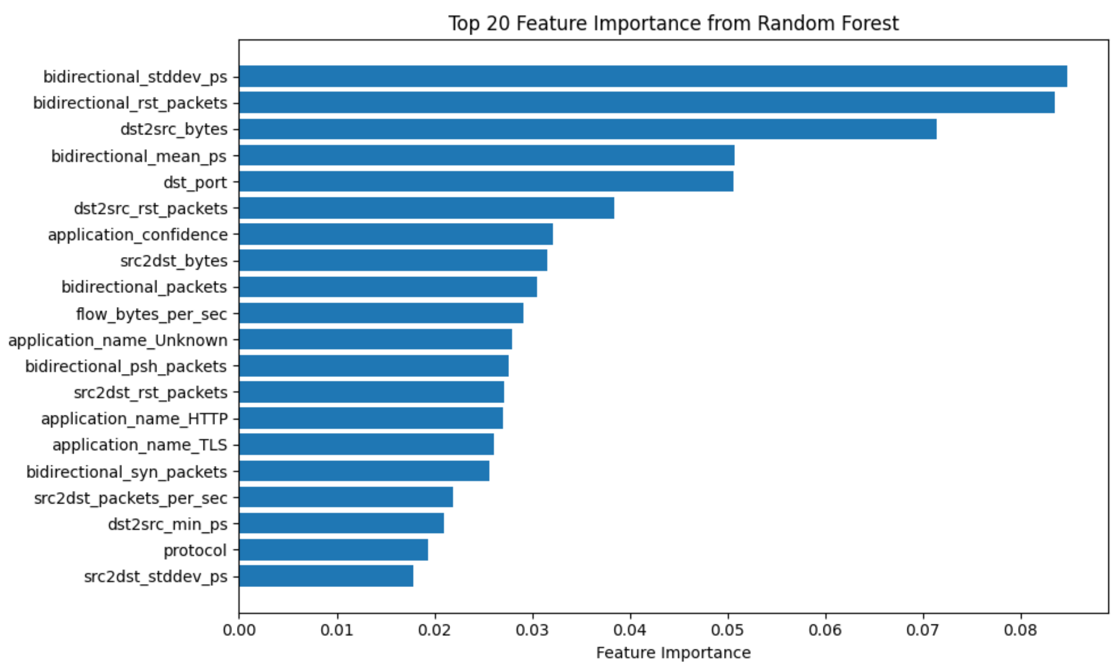
```
'application_category_name_Unspecified']
X_train.shape: (2332977, 307)
y_train.shape: (2332977,)
X_test.shape: (583245, 307)
y_test.shape: (583245,)
```

[3]:

```python
# 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. Performance validation with different feature counts
print("\nStep 3: Performance evaluation with different feature counts")
if dev_mode:
    target_features_list = [5, 10]
else:
    target_features_list = [5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65,␣
↪70, 75, 80, 85, 90, 95, 100]
results_comparison = []

for n_features in target_features_list:
    print(f"\nValidating with {n_features} features")

    # select top n_features based on F-scores
    top_features = importance_df.head(n_features)['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]
    X_val_split_selected = X_val_split[top_features]

    # Validate model for selected features
    try:
        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_val = test_rf.predict(X_val_split_selected)

        y_true_binary = (y_val_split != NORMAL_LABEL).astype(int)  # normal: 0,␣
↪anomaly: 1
        y_pred_binary = (y_pred_val != NORMAL_LABEL).astype(int)   # normal: 0,␣
↪anomaly: 1

        precision = precision_score(y_true_binary, y_pred_binary,␣
↪zero_division=0)
```

```python
        recall = recall_score(y_true_binary, y_pred_binary, zero_division=0)
        f1 = f1_score(y_true_binary, y_pred_binary, zero_division=0)

        # Normal and anomaly detection rates
        normal_total = np.sum(y_true_binary == 0)
        anomaly_total = np.sum(y_true_binary == 1)

        if normal_total > 0:
            normal_detection_rate = np.sum((y_true_binary == 0) &␣
↪(y_pred_binary == 0)) / normal_total
        else:
            normal_detection_rate = 0.0

        if anomaly_total > 0:
            anomaly_detection_rate = np.sum((y_true_binary == 1) &␣
↪(y_pred_binary == 1)) / anomaly_total
        else:
            anomaly_detection_rate = 0.0

        # outlier fraction
        outlier_fraction = np.sum(y_pred_val == -1) / len(y_pred_val)

        results_comparison.append({
            'n_features': n_features,
            'precision': precision,
            'recall': recall,
            'f1_score': f1,
            'normal_detection_rate': normal_detection_rate,
            'anomaly_detection_rate': anomaly_detection_rate,
            'outlier_fraction': outlier_fraction
        })

        print(f"  F1: {f1:.4f}, Normal Det.: {normal_detection_rate:.4f}, "
            f"Anomaly Det.: {anomaly_detection_rate:.4f}, Outlier:␣
↪{outlier_fraction:.4f}")

    except Exception as e:
        print(f"  Error: {e}")
        results_comparison.append({
            'n_features': n_features,
            'precision': 0.0,
            'recall': 0.0,
            'f1_score': 0.0,
            'normal_detection_rate': 0.0,
            'anomaly_detection_rate': 0.0,
            'outlier_fraction': 0.0, 'training_samples': 0
        })
```

```
print(f"\nCompleted evaluation for {len(results_comparison)} feature␣
↪configurations.")

# isualization and analysis
print("Results visualization")

results_df = pd.DataFrame(results_comparison)
print("\nResults Summary:")
print(results_df.round(4))

fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2, figsize=(16, 12))

# F1-Score
ax1.plot(results_df['n_features'], results_df['f1_score'], 'bo-', linewidth=2,␣
↪markersize=8)
ax1.set_xlabel('Number of Features')
ax1.set_ylabel('F1 Score')
ax1.set_title('OneClass SVM: F1 Score vs Number of Features')
ax1.grid(True, alpha=0.3)
ax1.set_ylim(0, 1)

# Detection Rates
ax2.plot(results_df['n_features'], results_df['normal_detection_rate'], 'go-',
         label='Normal Detection Rate', linewidth=2, markersize=8)
ax2.plot(results_df['n_features'], results_df['anomaly_detection_rate'], 'ro-',
         label='Anomaly Detection Rate', linewidth=2, markersize=8)
ax2.set_xlabel('Number of Features')
ax2.set_ylabel('Detection Rate')
ax2.set_title('OneClass SVM: Detection Rates vs Number of Features')
ax2.legend()
ax2.grid(True, alpha=0.3)
ax2.set_ylim(0, 1)

# Precision vs Recall
ax3.plot(results_df['n_features'], results_df['precision'], 'mo-',
         label='Precision', linewidth=2, markersize=8)
ax3.plot(results_df['n_features'], results_df['recall'], 'co-',
         label='Recall', linewidth=2, markersize=8)
ax3.set_xlabel('Number of Features')
ax3.set_ylabel('Score')
ax3.set_title('OneClass SVM: Precision/Recall vs Number of Features')
ax3.legend()
ax3.grid(True, alpha=0.3)
ax3.set_ylim(0, 1)

# Outlier Fraction
```

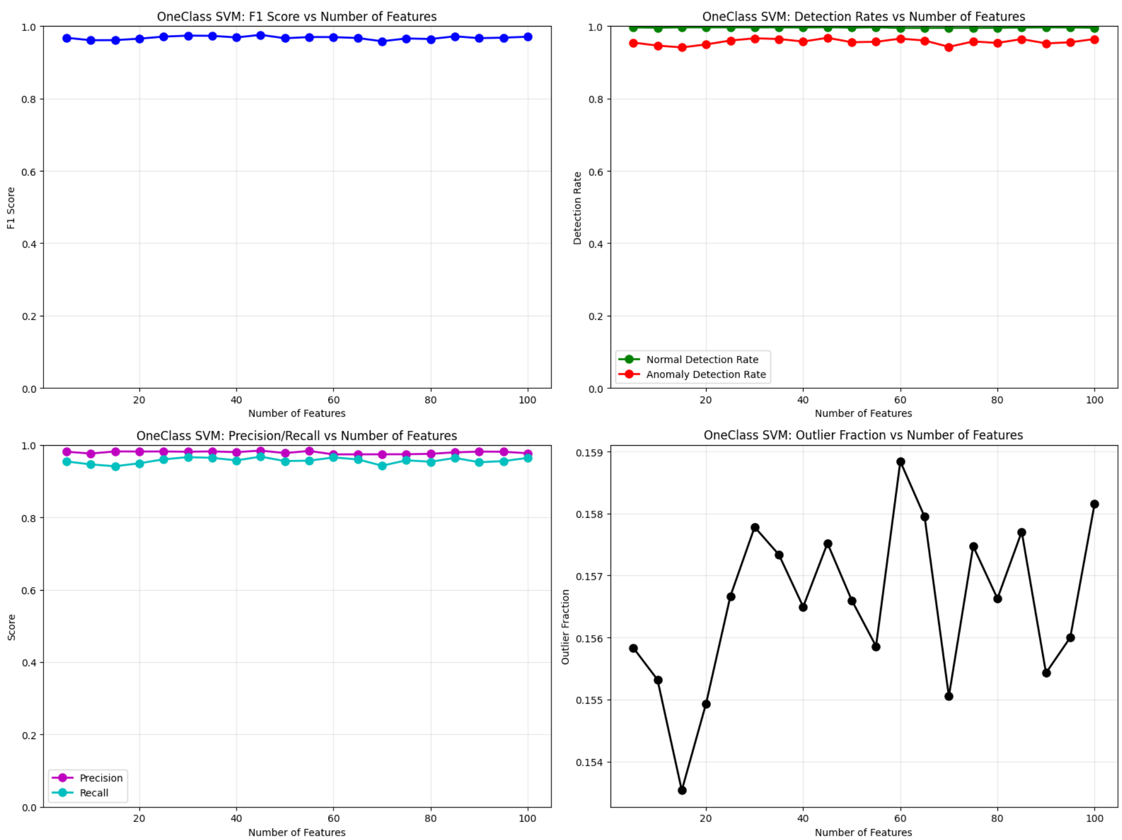
```python
ax4.plot(results_df['n_features'], results_df['outlier_fraction'], 'ko-',
         linewidth=2, markersize=8)
ax4.set_xlabel('Number of Features')
ax4.set_ylabel('Outlier Fraction')
ax4.set_title('OneClass SVM: Outlier Fraction vs Number of Features')
ax4.grid(True, alpha=0.3)

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

print("Optimal feature selection")

# Calculate balanced score
results_df['balanced_score'] = (
    results_df['f1_score'] +
    results_df['normal_detection_rate'] +
    results_df['anomaly_detection_rate']
) / 3

# NaN values handling
valid_results = results_df[results_df['balanced_score'] > 0]

if len(valid_results) > 0:
    best_idx = valid_results['balanced_score'].idxmax()
    best_result = valid_results.loc[best_idx]

    optimal_n_features = int(best_result['n_features'])
    optimal_features_list = importance_df.head(optimal_n_features)['feature'].
 ↪tolist()

    print(f"Optimal number of features: {optimal_n_features}")
    print(f"F1 Score: {best_result['f1_score']:.4f}")
    print(f"Normal Detection Rate: {best_result['normal_detection_rate']:.4f}")
    print(f"Anomaly Detection Rate: {best_result['anomaly_detection_rate']:.
 ↪4f}")
    print(f"Balanced Score: {best_result['balanced_score']:.4f}")
    print(f"Outlier Fraction: {best_result['outlier_fraction']:.4f}")

    print("\nSelected features for OneClass SVM:")
    for i, (_, row) in enumerate(importance_df.head(optimal_n_features).
 ↪iterrows(), 1):
        print(f"{i:2d}. {row['feature']:<35} {row['importance']:.4f}")

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

print(f"\nX_train_optimal.shape: {X_train_optimal.shape}")
```

```python
print(f"X_test_optimal.shape: {X_test_optimal.shape}")
```

```
Step 3: Performance evaluation with different feature counts

Validating with 5 features
  F1: 0.9678, Normal Det.: 0.9966, Anomaly Det.: 0.9546, Outlier: 0.1558

Validating with 10 features
  F1: 0.9611, Normal Det.: 0.9956, Anomaly Det.: 0.9464, Outlier: 0.1553

Validating with 15 features
  F1: 0.9613, Normal Det.: 0.9968, Anomaly Det.: 0.9413, Outlier: 0.1535

Validating with 20 features
  F1: 0.9654, Normal Det.: 0.9967, Anomaly Det.: 0.9495, Outlier: 0.1549

Validating with 25 features
  F1: 0.9711, Normal Det.: 0.9967, Anomaly Det.: 0.9603, Outlier: 0.1567

Validating with 30 features
  F1: 0.9738, Normal Det.: 0.9965, Anomaly Det.: 0.9664, Outlier: 0.1578

Validating with 35 features
  F1: 0.9733, Normal Det.: 0.9967, Anomaly Det.: 0.9645, Outlier: 0.1573

Validating with 40 features
  F1: 0.9688, Normal Det.: 0.9963, Anomaly Det.: 0.9575, Outlier: 0.1565

Validating with 45 features
  F1: 0.9760, Normal Det.: 0.9971, Anomaly Det.: 0.9678, Outlier: 0.1575

Validating with 50 features
  F1: 0.9665, Normal Det.: 0.9959, Anomaly Det.: 0.9556, Outlier: 0.1566

Validating with 55 features
  F1: 0.9699, Normal Det.: 0.9969, Anomaly Det.: 0.9567, Outlier: 0.1559

Validating with 60 features
  F1: 0.9698, Normal Det.: 0.9951, Anomaly Det.: 0.9656, Outlier: 0.1588

Validating with 65 features
  F1: 0.9672, Normal Det.: 0.9951, Anomaly Det.: 0.9603, Outlier: 0.1579

Validating with 70 features
  F1: 0.9582, Normal Det.: 0.9952, Anomaly Det.: 0.9428, Outlier: 0.1551

Validating with 75 features
```

```
  F1: 0.9660, Normal Det.: 0.9952, Anomaly Det.: 0.9577, Outlier: 0.1575

Validating with 80 features
  F1: 0.9645, Normal Det.: 0.9954, Anomaly Det.: 0.9537, Outlier: 0.1566

Validating with 85 features
  F1: 0.9719, Normal Det.: 0.9962, Anomaly Det.: 0.9643, Outlier: 0.1577

Validating with 90 features
  F1: 0.9668, Normal Det.: 0.9966, Anomaly Det.: 0.9524, Outlier: 0.1554

Validating with 95 features
  F1: 0.9682, Normal Det.: 0.9965, Anomaly Det.: 0.9555, Outlier: 0.1560

Validating with 100 features
  F1: 0.9707, Normal Det.: 0.9957, Anomaly Det.: 0.9644, Outlier: 0.1582

Completed evaluation for 20 feature configurations.
Results visualization

Results Summary:
    n_features  precision  recall  f1_score  normal_detection_rate  \
0            5     0.9815  0.9546    0.9678                 0.9966
1           10     0.9763  0.9464    0.9611                 0.9956
2           15     0.9823  0.9413    0.9613                 0.9968
3           20     0.9819  0.9495    0.9654                 0.9967
4           25     0.9821  0.9603    0.9711                 0.9967
5           30     0.9814  0.9664    0.9738                 0.9965
6           35     0.9822  0.9645    0.9733                 0.9967
7           40     0.9803  0.9575    0.9688                 0.9963
8           45     0.9844  0.9678    0.9760                 0.9971
9           50     0.9777  0.9556    0.9665                 0.9959
10          55     0.9835  0.9567    0.9699                 0.9969
11          60     0.9740  0.9656    0.9698                 0.9951
12          65     0.9742  0.9603    0.9672                 0.9951
13          70     0.9742  0.9428    0.9582                 0.9952
14          75     0.9745  0.9577    0.9660                 0.9952
15          80     0.9756  0.9537    0.9645                 0.9954
16          85     0.9797  0.9643    0.9719                 0.9962
17          90     0.9818  0.9524    0.9668                 0.9966
18          95     0.9814  0.9555    0.9682                 0.9965
19         100     0.9771  0.9644    0.9707                 0.9957

    anomaly_detection_rate  outlier_fraction
0                   0.9546            0.1558
1                   0.9464            0.1553
2                   0.9413            0.1535
3                   0.9495            0.1549
```

4	0.9603	0.1567
5	0.9664	0.1578
6	0.9645	0.1573
7	0.9575	0.1565
8	0.9678	0.1575
9	0.9556	0.1566
10	0.9567	0.1559
11	0.9656	0.1588
12	0.9603	0.1579
13	0.9428	0.1551
14	0.9577	0.1575
15	0.9537	0.1566
16	0.9643	0.1577
17	0.9524	0.1554
18	0.9555	0.1560
19	0.9644	0.1582




```
Optimal feature selection
Optimal number of features: 45
F1 Score: 0.9760
Normal Detection Rate: 0.9971
```

```
Anomaly Detection Rate: 0.9678
Balanced Score: 0.9803
Outlier Fraction: 0.1575

Selected features for OneClass SVM:
 1. bidirectional_stddev_ps          0.0847
 2. bidirectional_rst_packets        0.0835
 3. dst2src_bytes                    0.0715
 4. bidirectional_mean_ps            0.0508
 5. dst_port                         0.0506
 6. dst2src_rst_packets              0.0384
 7. application_confidence           0.0321
 8. src2dst_bytes                    0.0316
 9. bidirectional_packets            0.0306
10. flow_bytes_per_sec               0.0291
11. application_name_Unknown         0.0279
12. bidirectional_psh_packets        0.0276
13. src2dst_rst_packets              0.0272
14. application_name_HTTP            0.0271
15. application_name_TLS             0.0261
16. bidirectional_syn_packets        0.0257
17. src2dst_packets_per_sec          0.0219
18. dst2src_min_ps                   0.0209
19. protocol                         0.0193
20. src2dst_stddev_ps                0.0178
21. src2dst_mean_ps                  0.0169
22. flow_packets_per_sec             0.0165
23. bidirectional_fin_packets        0.0163
24. dst2src_packets_per_sec          0.0162
25. src2dst_psh_packets              0.0152
26. dst2src_psh_packets              0.0133
27. dst2src_fin_packets              0.0131
28. bidirectional_max_piat_ms        0.0117
29. dst2src_mean_piat_ms             0.0113
30. dst2src_max_piat_ms              0.0105
31. bidirectional_min_piat_ms        0.0103
32. down_up_ratio                    0.0101
33. bidirectional_min_ps             0.0096
34. bidirectional_duration_ms        0.0087
35. src2dst_min_ps                   0.0079
36. bidirectional_mean_piat_ms       0.0074
37. src2dst_stddev_piat_ms           0.0071
38. bidirectional_stddev_piat_ms     0.0062
39. dst2src_syn_packets              0.0058
40. src2dst_fin_packets              0.0056
41. application_is_guessed           0.0054
42. application_category_name_Web    0.0049
43. application_name_DNS             0.0043
```

```
44. dst2src_stddev_piat_ms             0.0043
45. src2dst_min_piat_ms                0.0042

X_train_optimal.shape: (2332977, 45)
X_test_optimal.shape: (583245, 45)
```

[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()
```

```python
    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=1,
min_samples_split=5, n_estimators=50, random_state=42; total time=  50.7s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=1,
min_samples_split=2, n_estimators=50, random_state=42; total time=  51.7s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=1,
min_samples_split=5, n_estimators=50, random_state=42; total time=  51.9s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=1,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.1min
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=2,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.1min
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=2,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.1min
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=1,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.1min
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=1,
min_samples_split=5, n_estimators=50, random_state=42; total time= 1.2min
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=1,
min_samples_split=2, n_estimators=100, random_state=42; total time= 1.7min
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=2,
min_samples_split=2, n_estimators=50, random_state=42; total time=  51.1s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=1,
min_samples_split=5, n_estimators=100, random_state=42; total time= 1.8min
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=1,
min_samples_split=5, n_estimators=100, random_state=42; total time= 1.8min
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=1,
min_samples_split=2, n_estimators=100, random_state=42; total time= 1.9min
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=1,
min_samples_split=2, n_estimators=100, random_state=42; total time= 2.1min
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=2,
min_samples_split=5, n_estimators=50, random_state=42; total time= 1.0min
```

```
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=2,
min_samples_split=5, n_estimators=50, random_state=42; total time= 1.1min
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=1,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.3min
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=2,
min_samples_split=5, n_estimators=50, random_state=42; total time= 1.2min
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=2,
min_samples_split=2, n_estimators=100, random_state=42; total time= 1.7min
[CV] END max_depth=5, max_features=log2, min_samples_leaf=1,
min_samples_split=2, n_estimators=50, random_state=42; total time=  45.3s
[CV] END max_depth=5, max_features=log2, min_samples_leaf=1,
min_samples_split=2, n_estimators=50, random_state=42; total time=  50.0s
[CV] END max_depth=5, max_features=log2, min_samples_leaf=1,
min_samples_split=2, n_estimators=50, random_state=42; total time=  46.1s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=2,
min_samples_split=2, n_estimators=100, random_state=42; total time= 1.7min
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=2,
min_samples_split=2, n_estimators=100, random_state=42; total time= 2.0min
[CV] END max_depth=5, max_features=log2, 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=log2, min_samples_leaf=1,
min_samples_split=5, n_estimators=50, random_state=42; total time=  52.5s
[CV] END max_depth=5, max_features=log2, min_samples_leaf=1,
min_samples_split=5, n_estimators=50, random_state=42; total time=  46.9s
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.2min
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 1.8min
[CV] END max_depth=5, max_features=sqrt, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 1.8min
[CV] END max_depth=5, max_features=log2, min_samples_leaf=2,
min_samples_split=2, n_estimators=50, random_state=42; total time=  44.6s
[CV] END max_depth=5, max_features=log2, min_samples_leaf=2,
min_samples_split=2, n_estimators=50, random_state=42; total time=  44.6s
[CV] END max_depth=5, max_features=log2, min_samples_leaf=1,
min_samples_split=2, n_estimators=100, random_state=42; total time= 1.5min
[CV] END max_depth=5, max_features=log2, min_samples_leaf=1,
min_samples_split=2, n_estimators=100, random_state=42; total time= 1.6min
[CV] END max_depth=5, max_features=log2, min_samples_leaf=2,
min_samples_split=2, n_estimators=50, random_state=42; total time=  43.5s
[CV] END max_depth=5, max_features=log2, min_samples_leaf=1,
min_samples_split=5, n_estimators=100, random_state=42; total time= 1.5min
[CV] END max_depth=5, max_features=log2, min_samples_leaf=1,
min_samples_split=5, n_estimators=100, random_state=42; total time= 1.4min
[CV] END max_depth=5, max_features=log2, min_samples_leaf=2,
min_samples_split=5, n_estimators=50, random_state=42; total time=  41.9s
[CV] END max_depth=5, max_features=log2, min_samples_leaf=1,
min_samples_split=2, n_estimators=100, random_state=42; total time= 1.9min
```

```
[CV] END max_depth=5, max_features=log2, min_samples_leaf=2,
min_samples_split=5, n_estimators=50, random_state=42; total time=  42.9s
[CV] END max_depth=5, max_features=log2, min_samples_leaf=1,
min_samples_split=5, n_estimators=100, random_state=42; total time= 1.7min
[CV] END max_depth=5, 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=5, max_features=log2, min_samples_leaf=2,
min_samples_split=2, n_estimators=100, random_state=42; total time= 1.4min
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=1,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.1min
[CV] END max_depth=5, max_features=log2, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 1.5min
[CV] END max_depth=5, max_features=log2, min_samples_leaf=2,
min_samples_split=2, n_estimators=100, random_state=42; total time= 2.0min
[CV] END max_depth=5, 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=7, max_features=sqrt, min_samples_leaf=1,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.2min
[CV] END max_depth=5, max_features=log2, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 1.5min
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=1,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.3min
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=1,
min_samples_split=5, n_estimators=50, random_state=42; total time= 1.2min
[CV] END max_depth=5, max_features=log2, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 1.8min
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=1,
min_samples_split=5, n_estimators=50, random_state=42; total time= 1.2min
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=1,
min_samples_split=5, n_estimators=50, random_state=42; total time= 1.2min
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=2,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.1min
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=1,
min_samples_split=2, n_estimators=100, random_state=42; total time= 2.3min
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=1,
min_samples_split=2, n_estimators=100, random_state=42; total time= 2.3min
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=2,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.3min
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=1,
min_samples_split=2, n_estimators=100, random_state=42; total time= 2.6min
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=2,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.6min
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=2,
min_samples_split=5, n_estimators=50, random_state=42; total time= 1.1min
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=2,
min_samples_split=5, n_estimators=50, random_state=42; total time= 1.2min
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=1,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.3min
```

```
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=1,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.3min
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=2,
min_samples_split=5, n_estimators=50, random_state=42; total time= 1.2min
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=2,
min_samples_split=2, n_estimators=100, random_state=42; total time= 2.2min
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=2,
min_samples_split=2, n_estimators=100, random_state=42; total time= 2.2min
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=2,
min_samples_split=2, n_estimators=100, random_state=42; total time= 2.4min
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=1,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.8min
[CV] END max_depth=7, max_features=log2, min_samples_leaf=1,
min_samples_split=2, n_estimators=50, random_state=42; total time=  57.3s
[CV] END max_depth=7, max_features=log2, min_samples_leaf=1,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.4min
[CV] END max_depth=7, max_features=log2, min_samples_leaf=1,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.5min
[CV] END max_depth=7, max_features=log2, min_samples_leaf=1,
min_samples_split=5, n_estimators=50, random_state=42; total time=  58.5s
[CV] END max_depth=7, max_features=log2, min_samples_leaf=1,
min_samples_split=5, n_estimators=50, random_state=42; total time=  58.6s
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.3min
[CV] END max_depth=7, max_features=sqrt, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.3min
[CV] END max_depth=7, max_features=log2, min_samples_leaf=1,
min_samples_split=2, n_estimators=100, random_state=42; total time= 1.9min
[CV] END max_depth=7, max_features=log2, min_samples_leaf=1,
min_samples_split=5, n_estimators=50, random_state=42; total time= 1.3min
[CV] END max_depth=7, max_features=log2, min_samples_leaf=2,
min_samples_split=2, n_estimators=50, random_state=42; total time=  59.6s
[CV] END max_depth=7, max_features=log2, min_samples_leaf=1,
min_samples_split=2, n_estimators=100, random_state=42; total time= 1.9min
[CV] END max_depth=7, max_features=log2, min_samples_leaf=2,
min_samples_split=2, n_estimators=50, random_state=42; total time=  59.6s
[CV] END max_depth=7, max_features=log2, min_samples_leaf=1,
min_samples_split=2, n_estimators=100, random_state=42; total time= 1.9min
[CV] END max_depth=7, max_features=log2, min_samples_leaf=2,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.1min
[CV] END max_depth=7, 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=7, max_features=sqrt, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 3.3min
[CV] END max_depth=7, max_features=log2, min_samples_leaf=1,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.0min
[CV] END max_depth=7, max_features=log2, min_samples_leaf=1,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.0min
```

```
[CV] END max_depth=7, max_features=log2, min_samples_leaf=2,
min_samples_split=5, n_estimators=50, random_state=42; total time= 1.0min
[CV] END max_depth=7, 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=7, max_features=log2, min_samples_leaf=2,
min_samples_split=5, n_estimators=50, random_state=42; total time= 1.0min
[CV] END max_depth=7, max_features=log2, min_samples_leaf=2,
min_samples_split=2, n_estimators=100, random_state=42; total time= 2.0min
[CV] END max_depth=7, max_features=log2, min_samples_leaf=2,
min_samples_split=2, n_estimators=100, random_state=42; total time= 2.0min
[CV] END max_depth=7, max_features=log2, min_samples_leaf=2,
min_samples_split=2, n_estimators=100, random_state=42; total time= 2.0min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=1,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.4min
[CV] END max_depth=7, max_features=log2, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.0min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=1,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.4min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=1,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.5min
[CV] END max_depth=7, max_features=log2, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.0min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=1,
min_samples_split=5, n_estimators=50, random_state=42; total time= 1.4min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=1,
min_samples_split=5, n_estimators=50, random_state=42; total time= 1.4min
[CV] END max_depth=7, max_features=log2, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.7min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=1,
min_samples_split=5, n_estimators=50, random_state=42; total time= 1.4min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=2,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.4min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=2,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.4min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=2,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.4min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=1,
min_samples_split=2, n_estimators=100, random_state=42; total time= 3.4min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=2,
min_samples_split=5, n_estimators=50, random_state=42; total time= 1.4min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=2,
min_samples_split=5, n_estimators=50, random_state=42; total time= 1.4min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=1,
min_samples_split=2, n_estimators=100, random_state=42; total time= 3.4min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=1,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.8min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=1,
min_samples_split=2, n_estimators=100, random_state=42; total time= 3.6min
```

```
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=1,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.9min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=1,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.9min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=2,
min_samples_split=5, n_estimators=50, random_state=42; total time= 1.6min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=2,
min_samples_split=2, n_estimators=100, random_state=42; total time= 2.9min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=2,
min_samples_split=2, n_estimators=100, random_state=42; total time= 2.9min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=1,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.2min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=2,
min_samples_split=2, n_estimators=100, random_state=42; total time= 3.4min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=1,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.5min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=1,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.6min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=1,
min_samples_split=5, n_estimators=50, random_state=42; total time= 1.2min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.9min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.9min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=1,
min_samples_split=5, 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=5, n_estimators=50, random_state=42; total time= 1.7min
[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=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= 2.5min
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.9min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=2,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.3min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=2,
min_samples_split=2, n_estimators=50, random_state=42; total time= 1.3min
[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=5, n_estimators=50, random_state=42; total time= 1.1min
[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
```

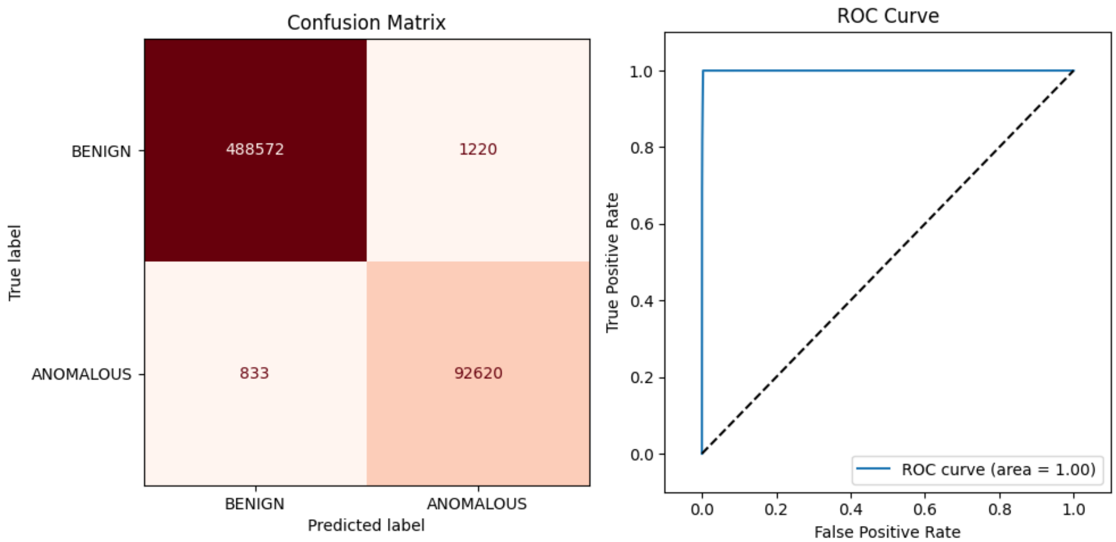
```
[CV] END max_depth=10, max_features=log2, min_samples_leaf=1,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.4min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=2,
min_samples_split=5, n_estimators=50, random_state=42; total time= 1.5min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=1,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.9min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=2,
min_samples_split=2, n_estimators=100, random_state=42; total time= 2.1min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=2,
min_samples_split=2, n_estimators=100, random_state=42; total time= 2.2min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=2,
min_samples_split=2, n_estimators=100, random_state=42; total time= 2.1min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.0min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.0min
[CV] END max_depth=10, max_features=log2, min_samples_leaf=2,
min_samples_split=5, n_estimators=100, random_state=42; total time= 2.1min
Grid search completed in 1185.86 seconds
Best parameters: {'max_depth': 10, 'max_features': 'sqrt', 'min_samples_leaf':
1, 'min_samples_split': 2, 'n_estimators': 50, 'random_state': 42}
Best CV score: 0.9968
```

[6]:

```python
# 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)
```

```python
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=50, max_depth=10,
min_samples_split=2, min_samples_leaf=1, max_features=sqrt, 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

[[488572   1220]
 [   833  92620]]
Precision: 0.987
Recall: 0.991
False Positive Rate: 0.002
False Negative Rate: 0.009
F1-Score: 0.989
Area under the curve: 1.000
```

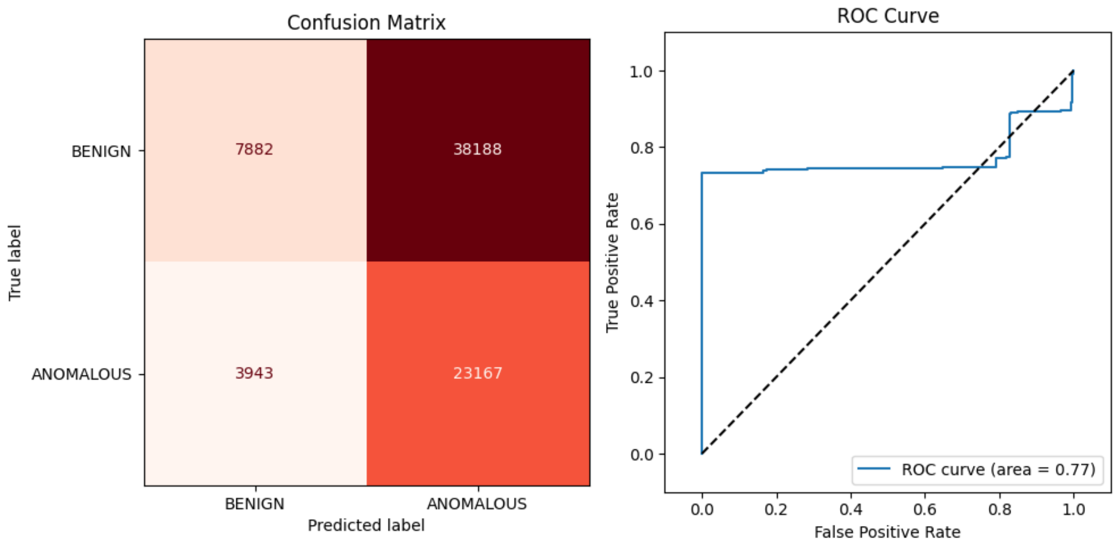


[7]:
```
# 6. Evaluate with tcpdump data
print("\nStep 6: Evaluate with tcpdump data")
if os.path.exists(tcpdump_pkl_file_name):
    print(f"Loading dataframe from {os.path.basename(tcpdump_pkl_file_name)}")
    tcpdump_dataframe = pd.read_pickle(tcpdump_pkl_file_name)
else:
    print(f"Creating dataframe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

# Add new featueres:
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)
```

```python
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 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
```

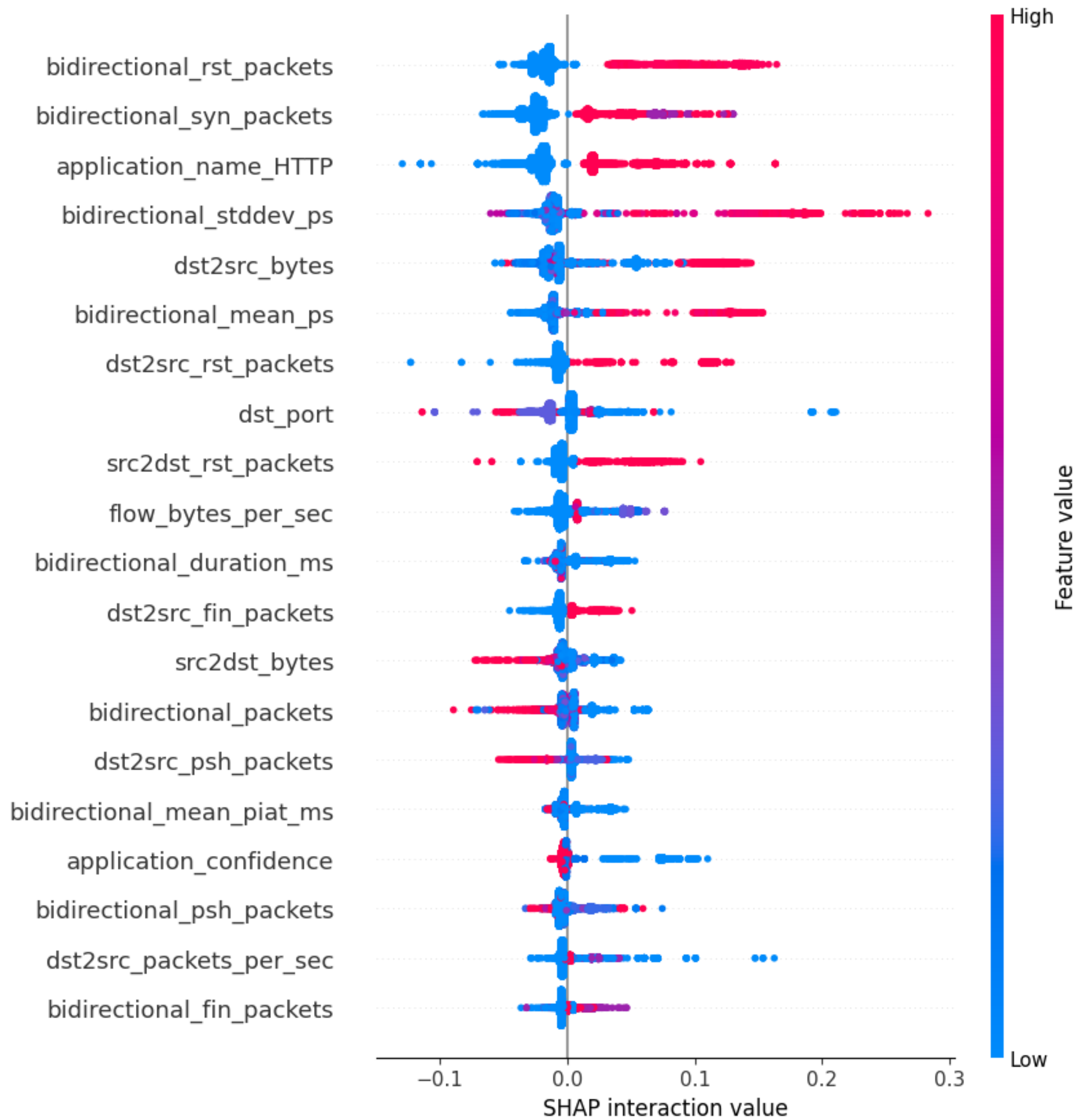
```
Splitting data into features (X) and labels (y)…
Cleaning data…
X_tcpdump.shape: (73180, 80)
y_tcpdump.shape: (73180,)
Handling categorical encoding…
Available categorical features: ['application_name',
'application_category_name']
Use categorical_encoder: OneHotEncoder(drop='first', handle_unknown='ignore',
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, 45)
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       0.67      0.17      0.27     46070
   ANOMALOUS       0.38      0.85      0.52     27110

    accuracy                           0.42     73180
   macro avg       0.52      0.51      0.40     73180
weighted avg       0.56      0.42      0.37     73180

[[ 7882 38188]
 [ 3943 23167]]
Precision: 0.378
Recall: 0.855
False Positive Rate: 0.829
False Negative Rate: 0.145
F1-Score: 0.524
Area under the curve: 0.769
```



[8]:

```python
# 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]:
```python
# 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_per_sec    0.016514
34        bidirectional_fin_packets    0.016263
50          dst2src_packets_per_sec    0.016198
36             src2dst_psh_packets    0.015190
42             dst2src_psh_packets    0.013289
44             dst2src_fin_packets    0.013115
20        bidirectional_max_piat_ms    0.011659
25            dst2src_mean_piat_ms    0.011323
27             dst2src_max_piat_ms    0.010478
17        bidirectional_min_piat_ms    0.010314
51                   down_up_ratio    0.010100
10            bidirectional_min_ps    0.009580
6         bidirectional_duration_ms    0.008717
13                  src2dst_min_ps    0.007865
18       bidirectional_mean_piat_ms    0.007418
23          src2dst_stddev_piat_ms    0.007120
19     bidirectional_stddev_piat_ms    0.006235
39             dst2src_syn_packets    0.005799
38             src2dst_fin_packets    0.005566
45          application_is_guessed    0.005392
306   application_category_name_Web    0.004912
61             application_name_DNS    0.004312
26          dst2src_stddev_piat_ms    0.004255
21             src2dst_min_piat_ms    0.004207
```

[ ]:

```
model_dir = os.path.join(project_root, 'models', 'rf')
if not os.path.exists(model_dir):
    os.makedirs(model_dir)
    print("Created model directory: models/rf")
```

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

```
Created model directory: models/rf
Saving the model to model.pkl
Model saved successfully.
Saving the encoder to encoder.pkl
Encoder saved successfully.
Saving the importance DataFrame to importance_df.pkl
Importance DataFrame saved successfully.
Saving the optimal features list to optimal_features_list.pkl
Optimal features list saved successfully.
```