In [64]:
```python
# ===========================
# IMPORT LIBRARIES
# ===========================

import pandas as pd
import numpy as np

from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

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

In [65]:
```python
# ===========================
# LOAD DATASET
# ===========================

df = pd.read_csv("balanceddata.csv")

print("Shape:", df.shape)
df.head()
```

```
Shape: (1061, 79)
```

Out[65]:

	Destination Port	Flow Duration	Total Fwd Packets	Total Backward Packets	Total Length of Fwd Packets	Total Length of Bwd Packets	Fwd Packet Length Max	Fwd Packet Length Min	Fwd Packet Length Mean	Fwd Packet Length Std	...	min_seg_size_fo
0	53	204	2	2	60	316	30	30	30.0	0.000000	...	
1	80	3	2	0	0	0	0	0	0.0	0.000000	...	
2	80	63163100	7	0	0	0	0	0	0.0	0.000000	...	
3	21	270	2	1	14	0	14	0	7.0	9.899495	...	
4	1782	57	1	1	2	6	2	2	2.0	0.000000	...	

5 rows × 79 columns

In [67]:
```python
# ===========================
# CREATE BINARY + ATTACK TYPE LABELS
# ===========================

# Keep original attack type
df["AttackType"] = df[" Label"]   # preserve string classes

# Create binary label: BENIGN = 0, all others = 1
df["BinaryLabel"] = df[" Label"].apply(lambda x: 0 if x.strip() == "BENIGN" else 1)
```

In [68]:
```python
# ===========================
# ENCODE ATTACK TYPE ONLY
# ===========================

# LabelEncoder ONLY for multiclass attack type
attack_encoder = LabelEncoder()
df["AttackTypeEncoded"] = attack_encoder.fit_transform(df["AttackType"])

# No need to encode BinaryLabel (already 0/1)
# No other object columns in balanceddata.csv require encoding
```

In [69]:

```python
# ===========================
# FEATURE / LABEL SEPARATION
# ===========================

# Columns to drop (label fields)
label_cols = [" Label", "BinaryLabel", "AttackType", "AttackTypeEncoded"]

# Feature matrix (all numeric features only)
X = df.drop(columns=label_cols)

# Targets
y_binary = df["BinaryLabel"]                    # For 0/1 attack detection
y_attack = df["AttackTypeEncoded"]              # For multiclass attack-type prediction
```

In [70]:

```python
# ---------- Robust Preprocessing for balanceddata.csv ----------
import numpy as np
import pandas as pd
from sklearn.preprocessing import StandardScaler

# 0) Ensure label-related columns exist
expected_labels = [" Label", "BinaryLabel", "AttackType", "AttackTypeEncoded"]
for c in expected_labels:
    if c not in df.columns:
        raise ValueError(f"Expected column '{c}' not found in df.columns. Please run the label creation step

# 1) Build X_df by dropping label columns (keep only numeric features)
label_cols = [" Label", "BinaryLabel", "AttackType", "AttackTypeEncoded"]
X_df = df.drop(columns=label_cols).copy()
print("Initial feature shape (before cleaning):", X_df.shape)

# 2) Diagnostics: show non-numeric columns and counts of inf / -inf / NaN
def diagnostics(X_df, show_top=10):
    print("Shape:", X_df.shape)
    non_numeric = X_df.select_dtypes(exclude=[np.number]).columns.tolist()
    print("Non-numeric columns ({}): {}".format(len(non_numeric), non_numeric[:show_top]))
    nan_counts = X_df.isna().sum()
    posinf = np.isposinf(X_df.to_numpy()).sum(axis=0)
    neginf = np.isneginf(X_df.to_numpy()).sum(axis=0)
    report = []
    for i, col in enumerate(X_df.columns):
        n_nan = int(nan_counts[col])
        n_pos = int(posinf[i]) if hasattr(posinf, '__len__') else 0
        n_neg = int(neginf[i]) if hasattr(neginf, '__len__') else 0
        if (n_nan + n_pos + n_neg) > 0:
            report.append((col, n_nan, n_pos, n_neg))
    print("Columns with NaN/inf (showing up to {}) :".format(show_top))
    for r in report[:show_top]:
        print("  {:40s}  NaN:{:6d}  +inf:{:6d}  -inf:{:6d}".format(r[0], r[1], r[2], r[3]))
    print("Total problematic columns:", len(report))

diagnostics(X_df, show_top=30)

# 3) Convert any remaining non-numeric columns to numeric (coerce -> NaN)
for col in X_df.select_dtypes(exclude=[np.number]).columns:
    X_df[col] = pd.to_numeric(X_df[col], errors='coerce')

# 4) Replace inf/-inf with NaN, then impute medians
X_arr = X_df.to_numpy(dtype=np.float64)  # ensure numeric numpy array
if not np.isfinite(X_arr).all():
    print("Found non-finite entries (NaN or inf). Replacing with np.nan before imputation.")
    X_arr[~np.isfinite(X_arr)] = np.nan

# Recreate DataFrame with same columns/index
X_df = pd.DataFrame(X_arr, columns=X_df.columns, index=X_df.index)

# Impute NaN with column median (robust)
medians = X_df.median()
X_df = X_df.fillna(medians)

# 5) OPTIONAL: Clip extreme outliers to percentile range (helps stabilise scaling)
LOW_P = 0.005
HIGH_P = 0.995
```

```python
lower = X_df.quantile(LOW_P)
upper = X_df.quantile(HIGH_P)
X_df = X_df.clip(lower=lower, upper=upper, axis=1)

# 6) Drop constant columns (zero variance) if any
nz_std = X_df.std()
const_cols = nz_std[nz_std == 0].index.tolist()
if len(const_cols) > 0:
    print("Dropping constant columns (zero std):", const_cols)
    X_df = X_df.drop(columns=const_cols)

# 7) Final sanity check — any remaining non-finite?
if not np.isfinite(X_df.to_numpy()).all():
    bad_count = (~np.isfinite(X_df.to_numpy())).sum()
    raise ValueError(f"Still found {bad_count} non-finite entries after cleaning. Inspect data.")

print("Preprocessing finished. Clean feature shape:", X_df.shape)

# 8) Scale ONCE and keep scaler for demo
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_df)

# Persist useful objects for downstream steps
X = X_scaled                 # numeric numpy array for model training
feature_names = X_df.columns.tolist()

print("Feature matrix scaled. dtype:", X.dtype, "shape:", X.shape)
# ----------------------------------------------------------------------
```

```
Initial feature shape (before cleaning): (1061, 78)
Shape: (1061, 78)
Non-numeric columns (0): []
Columns with NaN/inf (showing up to 30) :
  Flow Bytes/s                                 NaN:     1  +inf:     0  -inf:     0
   Flow Packets/s                              NaN:     0  +inf:     1  -inf:     0
Total problematic columns: 2
Found non-finite entries (NaN or inf). Replacing with np.nan before imputation.
Dropping constant columns (zero std): [' Bwd PSH Flags', ' Fwd URG Flags', ' Bwd URG Flags', ' RST Flag Coun
t', ' CWE Flag Count', ' ECE Flag Count', 'Fwd Avg Bytes/Bulk', ' Fwd Avg Packets/Bulk', ' Fwd Avg Bulk Rat
e', ' Bwd Avg Bytes/Bulk', ' Bwd Avg Packets/Bulk', 'Bwd Avg Bulk Rate']
Preprocessing finished. Clean feature shape: (1061, 66)
Feature matrix scaled. dtype: float64 shape: (1061, 66)
```

In [71]:
```python
# ==========================
# TRAIN-TEST SPLIT
# ==========================

X_train, X_test, y_binary_train, y_binary_test, y_attack_train, y_attack_test = train_test_split(
    X,
    y_binary,
    y_attack,
    test_size=0.2,
    random_state=42
)
```

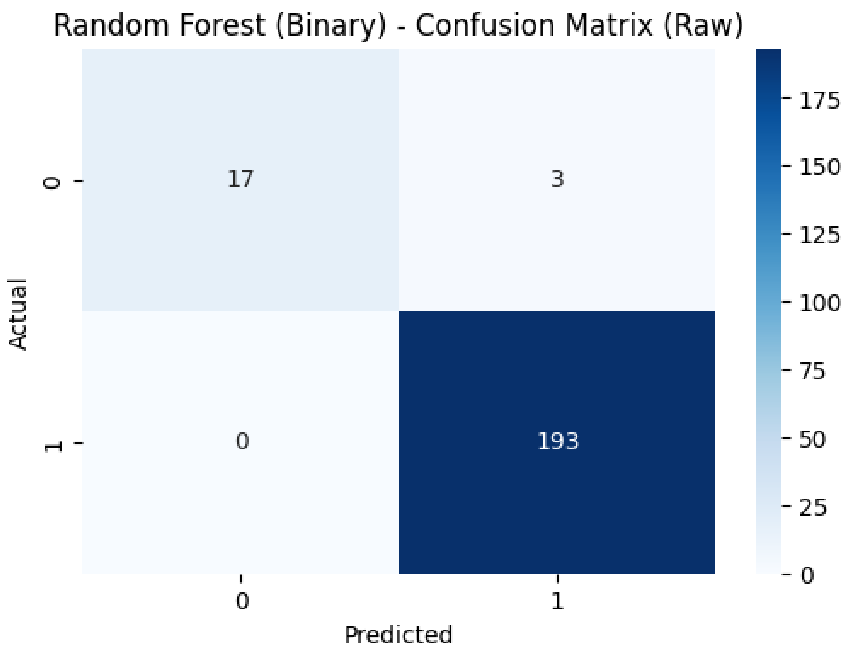
In [73]:
```python
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import (
    accuracy_score,
    confusion_matrix,
    classification_report,
    RocCurveDisplay,
    roc_curve,
    auc
)
from sklearn.multiclass import OneVsRestClassifier
from sklearn.preprocessing import label_binarize

print("\n======= RANDOM FOREST (BINARY + MULTICLASS) =======")
```

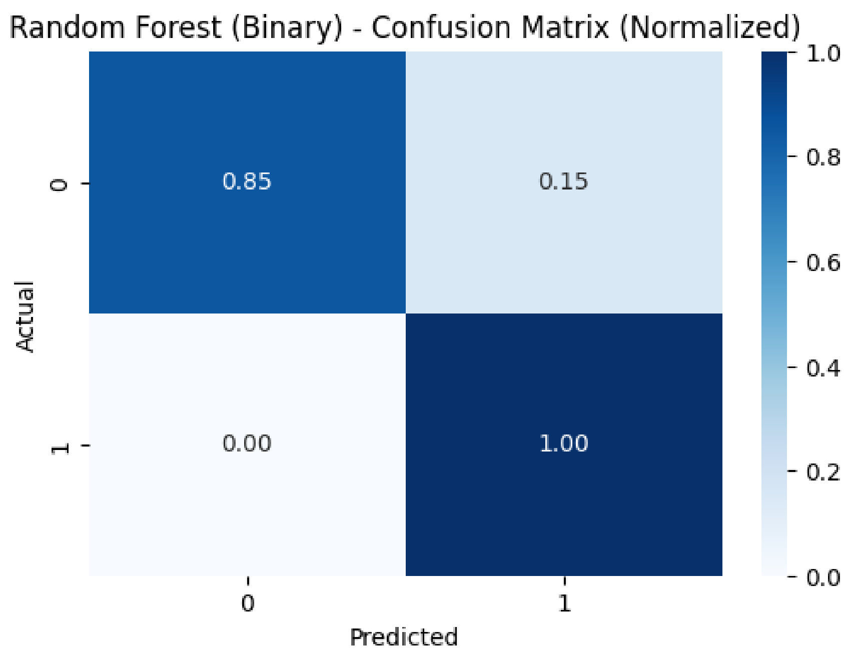
```python
# ---------------------------
# 1) RANDOM FOREST - BINARY (BENIGN vs ATTACK)
# ---------------------------
rf_binary = RandomForestClassifier(n_estimators=200, random_state=42, n_jobs=-1)
rf_binary.fit(X_train, y_binary_train)

# Predictions (binary)
pred_rf_bin = rf_binary.predict(X_test)

print("\n--- Binary classification (BENIGN=0 / ATTACK=1) ---")
print("Accuracy:", accuracy_score(y_binary_test, pred_rf_bin))
print("\nConfusion Matrix (raw):\n", confusion_matrix(y_binary_test, pred_rf_bin))
print("\nClassification Report:\n", classification_report(y_binary_test, pred_rf_bin, digits=4))

# Confusion matrix - raw
cm = confusion_matrix(y_binary_test, pred_rf_bin)
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title("Random Forest (Binary) - Confusion Matrix (Raw)")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

# Confusion matrix - normalized
cm_norm = confusion_matrix(y_binary_test, pred_rf_bin, normalize='true')
plt.figure(figsize=(6, 4))
sns.heatmap(cm_norm, annot=True, fmt='.2f', cmap='Blues')
plt.title("Random Forest (Binary) - Confusion Matrix (Normalized)")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

# ROC Curve (binary)
if len(np.unique(y_binary_test)) == 2:
    RocCurveDisplay.from_estimator(rf_binary, X_test, y_binary_test)
    plt.title("Random Forest (Binary) - ROC Curve")
    plt.show()

# ---------------------------
# 2) RANDOM FOREST - MULTICLASS (Attack type)
# ---------------------------
rf_multi = RandomForestClassifier(n_estimators=200, random_state=42, n_jobs=-1)
rf_multi.fit(X_train, y_attack_train)

# Predictions (multiclass)
pred_rf_attack = rf_multi.predict(X_test)

print("\n--- Multiclass Attack-Type classification ---")
print("Accuracy:", accuracy_score(y_attack_test, pred_rf_attack))
print("\nConfusion Matrix (raw):\n", confusion_matrix(y_attack_test, pred_rf_attack))
print("\nClassification Report:\n", classification_report(y_attack_test, pred_rf_attack, digits=4))

# Confusion matrix - raw (multiclass)
cm = confusion_matrix(y_attack_test, pred_rf_attack)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title("Random Forest (Multiclass) - Confusion Matrix (Raw)")
plt.xlabel("Predicted (encoded)")
plt.ylabel("Actual (encoded)")
plt.show()

# ---------------------------
# Multiclass ROC (One-vs-Rest) — robust plotting
# ---------------------------
print("\nMulticlass detected — plotting One-vs-Rest ROC curves (robust)")

# Fit One-vs-Rest wrapper and get probability matrix
clf_ovr = OneVsRestClassifier(RandomForestClassifier(n_estimators=200, random_state=42))
clf_ovr.fit(X_train, y_attack_train)
y_score = clf_ovr.predict_proba(X_test)  # shape: (n_samples, n_classes_ovr)
ovr_classes = np.array(clf_ovr.classes_)  # class order used by the classifier

# Binarize y_test using the exact same class ordering
```

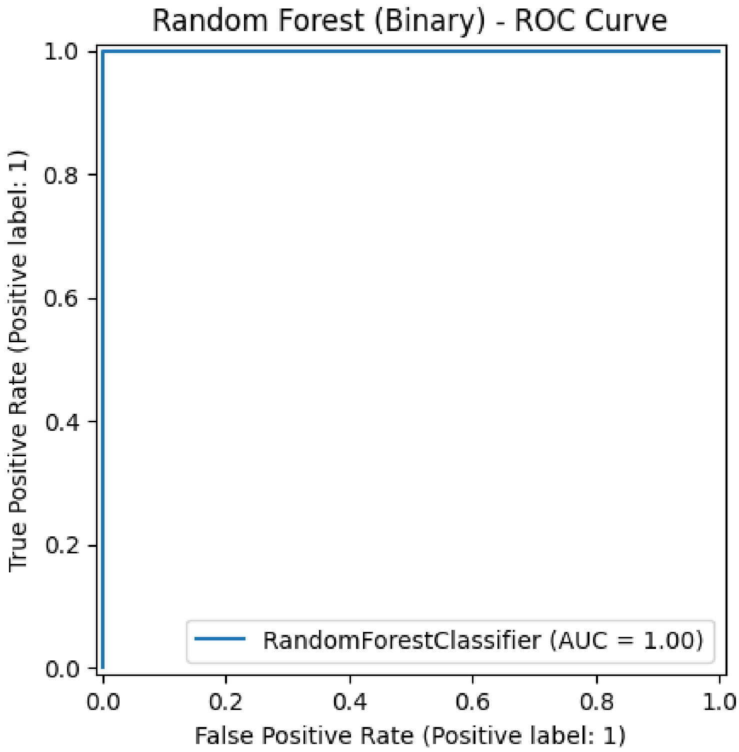
```
y_test_bin = label_binarize(y_attack_test, classes=ovr_classes)

# Defensive alignment (pad/truncate if shapes differ)
if y_test_bin.shape[1] < y_score.shape[1]:
    pad_cols = y_score.shape[1] - y_test_bin.shape[1]
    y_test_bin = np.hstack([y_test_bin, np.zeros((y_test_bin.shape[0], pad_cols), dtype=int)])
elif y_test_bin.shape[1] > y_score.shape[1]:
    y_test_bin = y_test_bin[:, :y_score.shape[1]]

# Try to map encoded classes to human-readable names if attack_encoder present
use_names = False
try:
    attack_encoder  # noqa: F821
    use_names = True
except NameError:
    use_names = False

def class_label(i):
    if use_names:
        try:
            return attack_encoder.inverse_transform([ovr_classes[i]])[0]
        except Exception:
            return str(ovr_classes[i])
    else:
        return str(ovr_classes[i])

plt.figure(figsize=(9, 7))
plotted_any = False
for i in range(y_score.shape[1]):
    # skip ROC if this class has no positive samples in y_test
    if np.sum(y_test_bin[:, i]) == 0:
        print(f"Skipping class {class_label(i)} — no positive samples in test set for this class.")
        continue
    try:
        fpr, tpr, _ = roc_curve(y_test_bin[:, i], y_score[:, i])
        auc_val = auc(fpr, tpr)
        plt.plot(fpr, tpr, label=f"{class_label(i)} (AUC = {auc_val:.2f})")
        plotted_any = True
    except Exception as e:
        print(f"Could not compute ROC for class {class_label(i)}: {e}")
        continue

if plotted_any:
    plt.plot([0, 1], [0, 1], 'k--')
    plt.title("Random Forest - ROC Curve (One-vs-Rest, attack-type)")
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.legend(loc='best', fontsize='small')
    plt.tight_layout()
    plt.show()
else:
    print("No per-class ROC curves were plotted (no usable positive samples in test set).")

# ---------------------------
# 3) FEATURE IMPORTANCE (from binary model)
# ---------------------------
importances = rf_binary.feature_importances_

# Use preserved feature_names (from preprocessing)
try:
    feature_names_used = feature_names
except NameError:
    # fallback: generate generic names
    feature_names_used = [f"Feature {i}" for i in range(X_train.shape[1])]

# Sort importance
sorted_idx = np.argsort(importances)

plt.figure(figsize=(8, max(6, len(sorted_idx)*0.15)))
sns.barplot(
    x=importances[sorted_idx],
    y=[feature_names_used[i] for i in sorted_idx],
    palette="viridis"
```

```
)
plt.title("Random Forest (Binary) - Feature Importances (Sorted)")
plt.xlabel("Importance")
plt.ylabel("Feature")
plt.tight_layout()
plt.show()
```

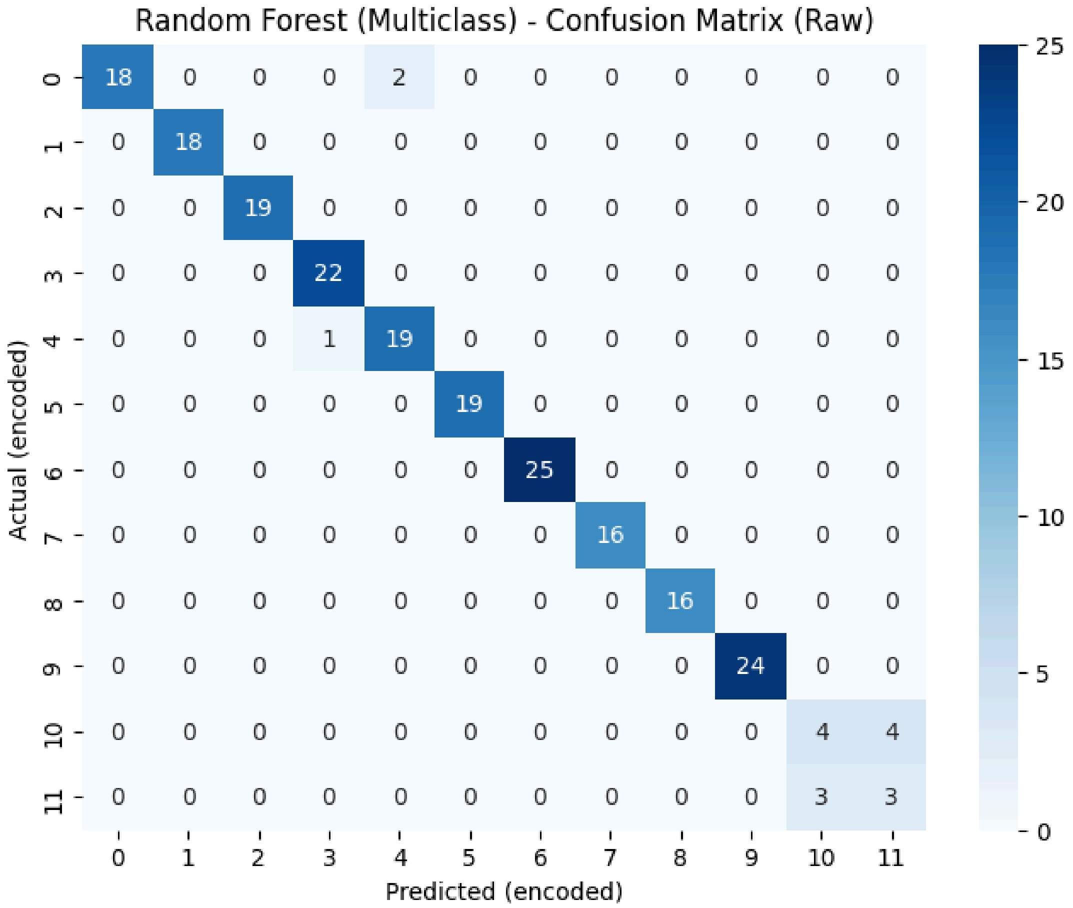
```
======= RANDOM FOREST (BINARY + MULTICLASS) =======

--- Binary classification (BENIGN=0 / ATTACK=1) ---
Accuracy: 0.9859154929577465

Confusion Matrix (raw):
 [[ 17   3]
 [  0 193]]

Classification Report:
              precision    recall  f1-score   support

           0     1.0000    0.8500    0.9189        20
           1     0.9847    1.0000    0.9923       193

    accuracy                         0.9859       213
   macro avg     0.9923    0.9250    0.9556       213
weighted avg     0.9861    0.9859    0.9854       213
```



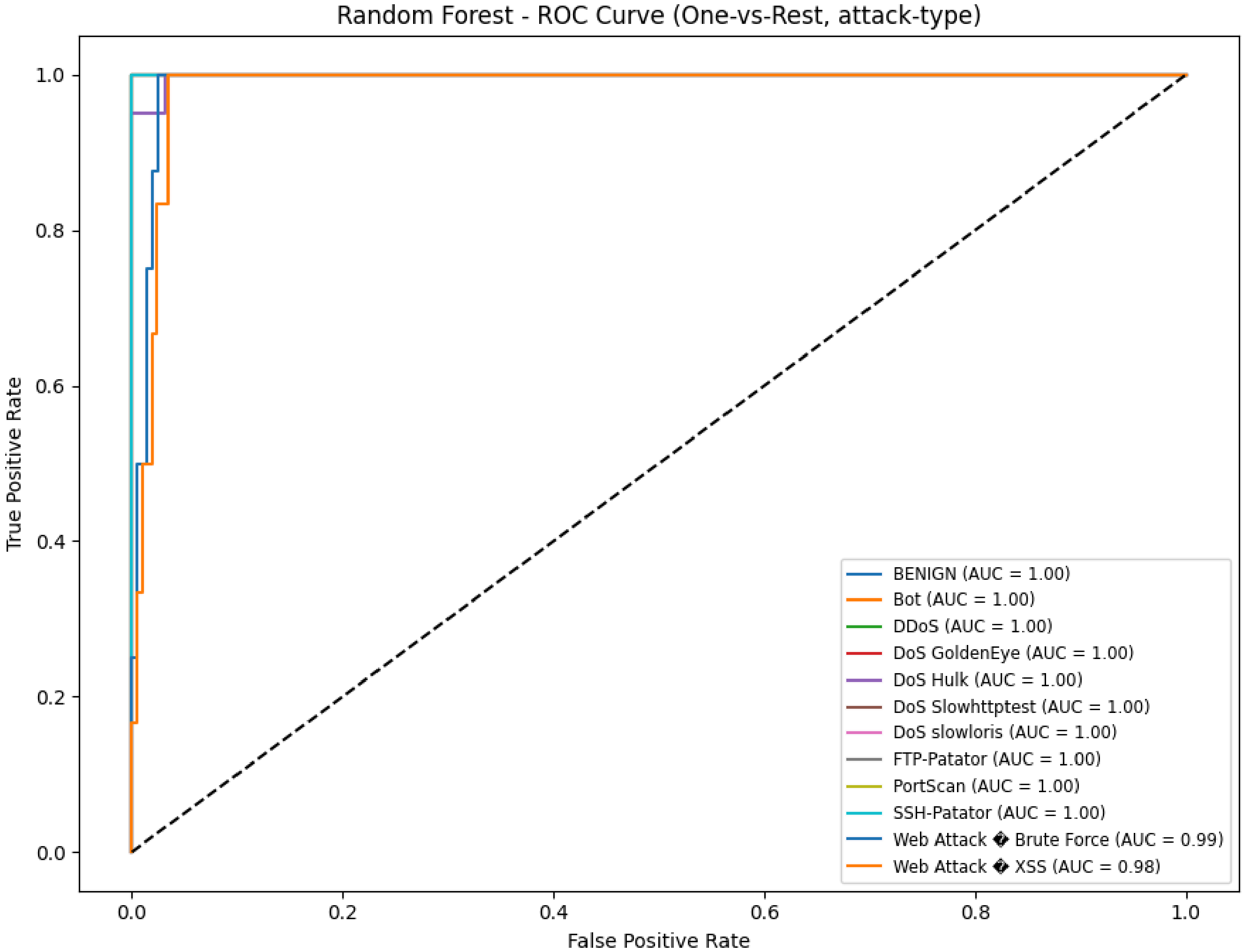


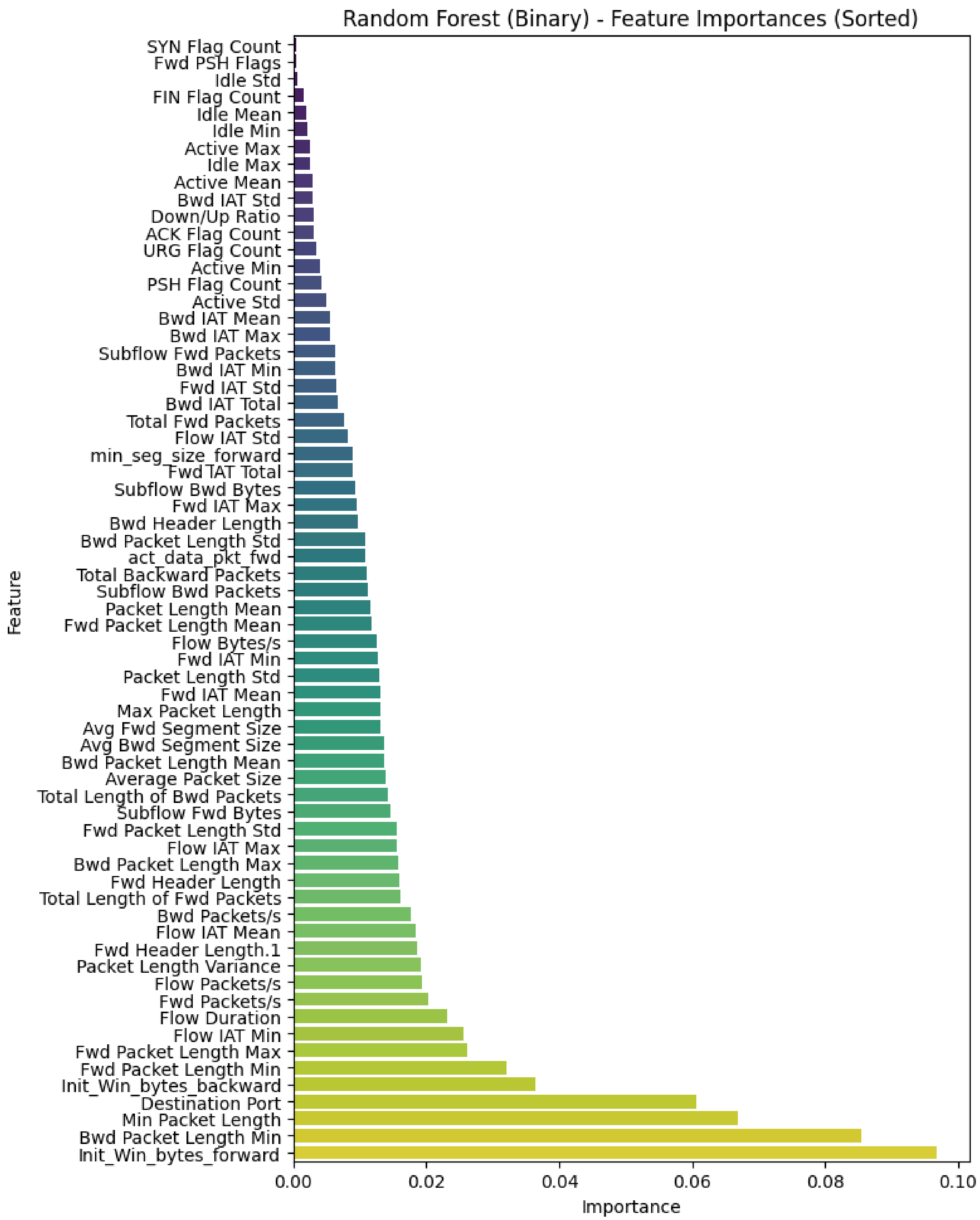



```
--- Multiclass Attack-Type classification ---
Accuracy: 0.9530516431924883

Confusion Matrix (raw):
 [[18  0  0  0  2  0  0  0  0  0  0  0]
 [ 0 18  0  0  0  0  0  0  0  0  0  0]
 [ 0  0 19  0  0  0  0  0  0  0  0  0]
 [ 0  0  0 22  0  0  0  0  0  0  0  0]
 [ 0  0  0  1 19  0  0  0  0  0  0  0]
 [ 0  0  0  0  0 19  0  0  0  0  0  0]
 [ 0  0  0  0  0  0 25  0  0  0  0  0]
 [ 0  0  0  0  0  0  0 16  0  0  0  0]
 [ 0  0  0  0  0  0  0  0 16  0  0  0]
 [ 0  0  0  0  0  0  0  0  0 24  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  4  4]
 [ 0  0  0  0  0  0  0  0  0  0  3  3]]

Classification Report:
              precision    recall  f1-score   support

           0     1.0000    0.9000    0.9474        20
           1     1.0000    1.0000    1.0000        18
           2     1.0000    1.0000    1.0000        19
           3     0.9565    1.0000    0.9778        22
           4     0.9048    0.9500    0.9268        20
           5     1.0000    1.0000    1.0000        19
           6     1.0000    1.0000    1.0000        25
           7     1.0000    1.0000    1.0000        16
           9     1.0000    1.0000    1.0000        16
          10     1.0000    1.0000    1.0000        24
          11     0.5714    0.5000    0.5333         8
          13     0.4286    0.5000    0.4615         6

    accuracy                         0.9531       213
   macro avg     0.9051    0.9042    0.9039       213
weighted avg     0.9544    0.9531    0.9532       213
```




```
Multiclass detected — plotting One-vs-Rest ROC curves (robust)
Skipping class Infiltration — no positive samples in test set for this class.
Skipping class Web Attack � Sql Injection — no positive samples in test set for this class.
```





In [75]:

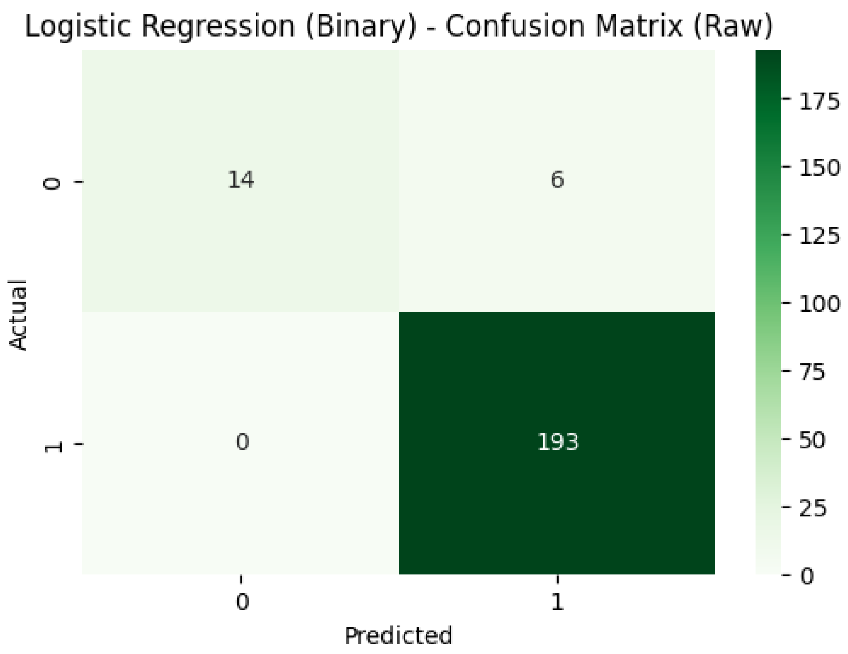
```
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import (
    accuracy_score,
    confusion_matrix,
    classification_report,
    RocCurveDisplay,
    roc_curve,
    auc
)
from sklearn.multiclass import OneVsRestClassifier
from sklearn.preprocessing import label_binarize
```

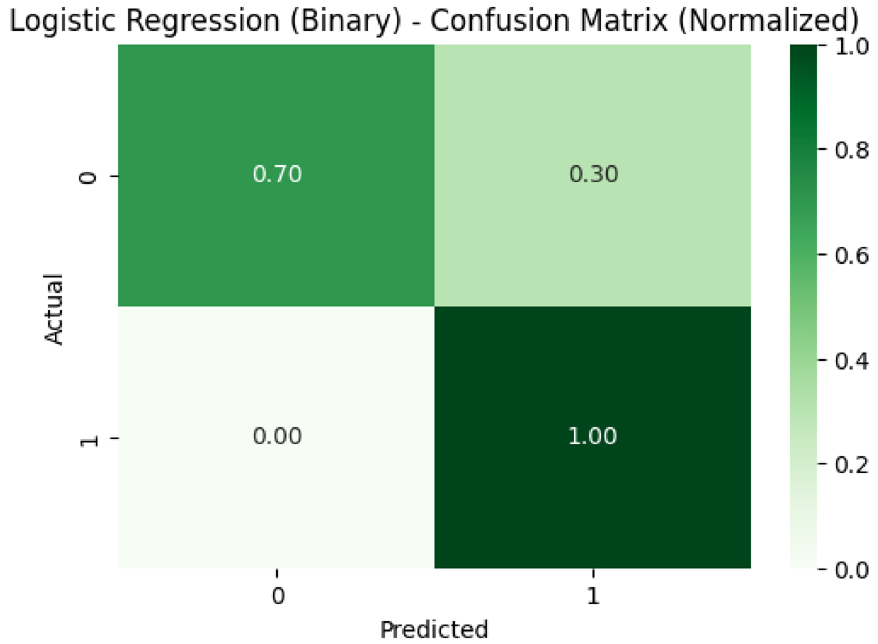
```python
print("\n======= LOGISTIC REGRESSION (BINARY + MULTICLASS) =======")

# ---------------------------
# 1) LOGISTIC REGRESSION - BINARY (BENIGN vs ATTACK)
# ---------------------------
lr_binary = LogisticRegression(max_iter=1000, solver='lbfgs', random_state=42)
lr_binary.fit(X_train, y_binary_train)

pred_lr_bin = lr_binary.predict(X_test)

print("\n--- Binary classification (BENIGN=0 / ATTACK=1) ---")
print("Accuracy:", accuracy_score(y_binary_test, pred_lr_bin))
print("\nConfusion Matrix (raw):\n", confusion_matrix(y_binary_test, pred_lr_bin))
print("\nClassification Report:\n", classification_report(y_binary_test, pred_lr_bin, digits=4))

# Confusion matrix (binary)
cm = confusion_matrix(y_binary_test, pred_lr_bin)
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Greens')
plt.title("Logistic Regression (Binary) - Confusion Matrix (Raw)")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

# Confusion matrix normalized
cm_norm = confusion_matrix(y_binary_test, pred_lr_bin, normalize='true')
plt.figure(figsize=(6, 4))
sns.heatmap(cm_norm, annot=True, fmt='.2f', cmap='Greens')
plt.title("Logistic Regression (Binary) - Confusion Matrix (Normalized)")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

# ROC curve (binary)
if len(np.unique(y_binary_test)) == 2:
    RocCurveDisplay.from_estimator(lr_binary, X_test, y_binary_test)
    plt.title("Logistic Regression (Binary) - ROC Curve")
    plt.show()

# ---------------------------
# 2) LOGISTIC REGRESSION - MULTICLASS (Attack type)
# ---------------------------
lr_multi = LogisticRegression(max_iter=1000, solver='lbfgs', multi_class='auto', random_state=42)
lr_multi.fit(X_train, y_attack_train)

pred_lr_attack = lr_multi.predict(X_test)

print("\n--- Multiclass Attack-Type classification ---")
print("Accuracy:", accuracy_score(y_attack_test, pred_lr_attack))
print("\nConfusion Matrix (raw):\n", confusion_matrix(y_attack_test, pred_lr_attack))
print("\nClassification Report:\n", classification_report(y_attack_test, pred_lr_attack, digits=4))

# Confusion matrix - raw (multiclass)
cm = confusion_matrix(y_attack_test, pred_lr_attack)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Greens')
plt.title("Logistic Regression (Multiclass) - Confusion Matrix (Raw)")
plt.xlabel("Predicted (encoded)")
plt.ylabel("Actual (encoded)")
plt.show()

# ---------------------------
# Multiclass ROC (Robust OVR)
# ---------------------------
print("\nMulticlass detected — plotting One-vs-Rest ROC curves (robust)")

clf_ovr = OneVsRestClassifier(LogisticRegression(max_iter=1000, solver='lbfgs'))
clf_ovr.fit(X_train, y_attack_train)
y_score = clf_ovr.predict_proba(X_test)
ovr_classes = np.array(clf_ovr.classes_)

y_test_bin = label_binarize(y_attack_test, classes=ovr_classes)
```

```python
# Align shapes if needed
if y_test_bin.shape[1] < y_score.shape[1]:
    pad = y_score.shape[1] - y_test_bin.shape[1]
    y_test_bin = np.hstack([y_test_bin, np.zeros((y_test_bin.shape[0], pad), dtype=int)])
elif y_test_bin.shape[1] > y_score.shape[1]:
    y_test_bin = y_test_bin[:, :y_score.shape[1]]

# Text names for classes
use_names = False
try:
    attack_encoder
    use_names = True
except:
    pass

def class_label(i):
    if use_names:
        try:
            return attack_encoder.inverse_transform([ovr_classes[i]])[0]
        except:
            return str(ovr_classes[i])
    else:
        return str(ovr_classes[i])

plt.figure(figsize=(9, 7))
plotted_any = False
for i in range(y_score.shape[1]):
    if np.sum(y_test_bin[:, i]) == 0:
        print(f"Skipping class {class_label(i)} — no positive samples in test set.")
        continue

    try:
        fpr, tpr, _ = roc_curve(y_test_bin[:, i], y_score[:, i])
        auc_val = auc(fpr, tpr)
        plt.plot(fpr, tpr, label=f"{class_label(i)} (AUC={auc_val:.2f})")
        plotted_any = True
    except:
        continue

if plotted_any:
    plt.plot([0, 1], [0, 1], 'k--')
    plt.title("Logistic Regression - ROC Curve (One-vs-Rest, Attack-Type)")
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.legend(fontsize='small')
    plt.tight_layout()
    plt.show()

# ---------------------------
# 3) FEATURE IMPORTANCE (Binary LR)
# ---------------------------
print("\n--- Feature Importance (Binary Logistic Regression) ---")

coef_binary = lr_binary.coef_[0]   # shape: (n_features,)
importance = np.abs(coef_binary)

sorted_idx = np.argsort(importance)

plt.figure(figsize=(8, max(6, len(sorted_idx)*0.15)))
sns.barplot(
    x=importance[sorted_idx],
    y=[feature_names[i] for i in sorted_idx],
    palette="summer"
)
plt.title("Logistic Regression (Binary) - Feature Importance (|coefficients|)")
plt.xlabel("Coefficient Magnitude")
plt.ylabel("Feature")
plt.tight_layout()
plt.show()

# ---------------------------
# 4) FEATURE IMPORTANCE (Multiclass LR)
```

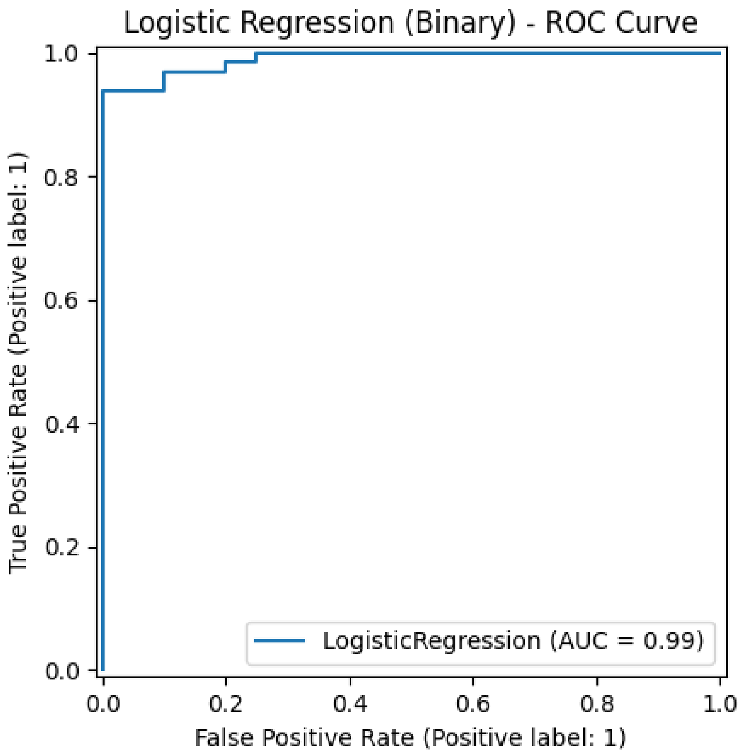
```python
# ---------------------------
print("\n--- Feature Importance (Multiclass Logistic Regression) ---")

coef_multi = np.mean(np.abs(lr_multi.coef_), axis=0)

sorted_idx = np.argsort(coef_multi)

plt.figure(figsize=(8, max(6, len(sorted_idx)*0.15)))
sns.barplot(
    x=coef_multi[sorted_idx],
    y=[feature_names[i] for i in sorted_idx],
    palette="viridis"
)
plt.title("Logistic Regression (Multiclass) - Feature Importance (Mean |coeffs|)")
plt.xlabel("Coefficient Magnitude")
plt.ylabel("Feature")
plt.tight_layout()
plt.show()
```

```
======= LOGISTIC REGRESSION (BINARY + MULTICLASS) =======

--- Binary classification (BENIGN=0 / ATTACK=1) ---
Accuracy: 0.971830985915493

Confusion Matrix (raw):
 [[ 14   6]
 [  0 193]]

Classification Report:
              precision    recall  f1-score   support

           0     1.0000    0.7000    0.8235        20
           1     0.9698    1.0000    0.9847       193

    accuracy                         0.9718       213
   macro avg     0.9849    0.8500    0.9041       213
weighted avg     0.9727    0.9718    0.9696       213
```



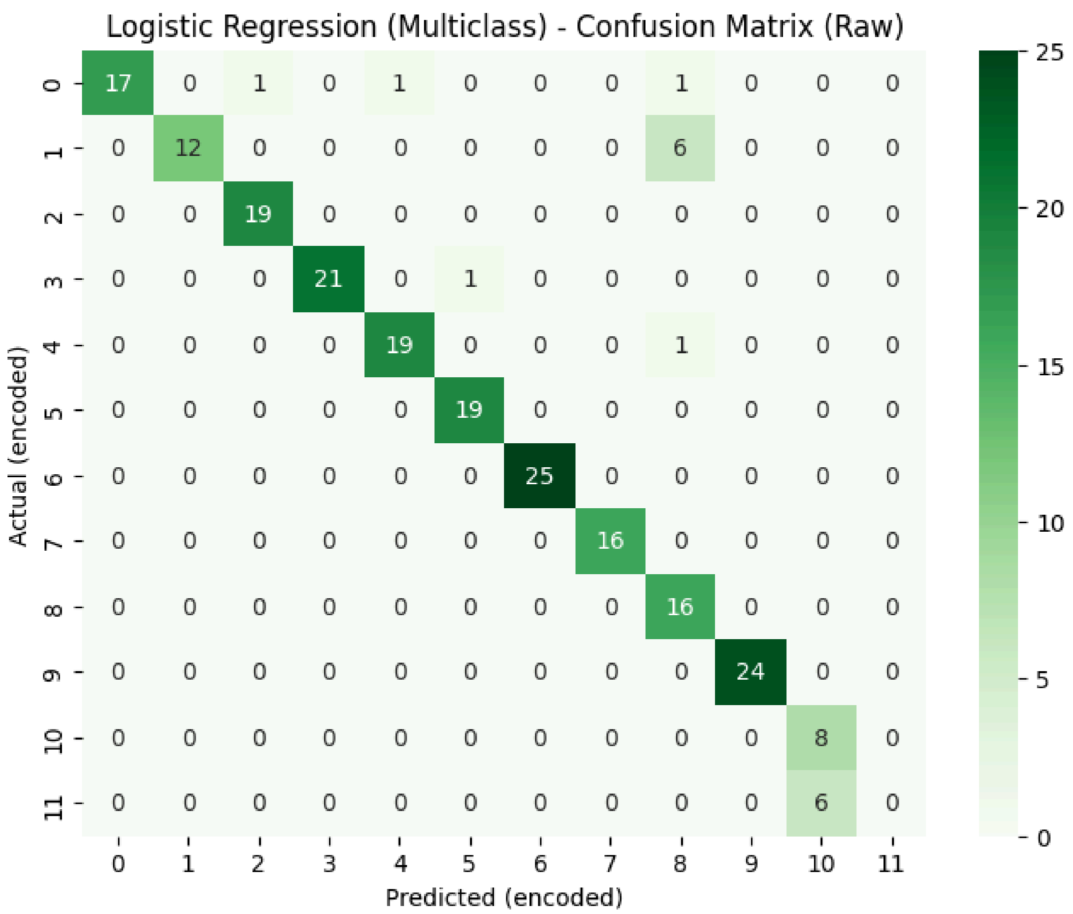


Logistic Regression (Binary) - Confusion Matrix (Normalized)
0.70
0.30
0.00
1.00
Actual
Predicted
0
1
0
1
1.0
0.8
0.6
0.4
0.2
0.0

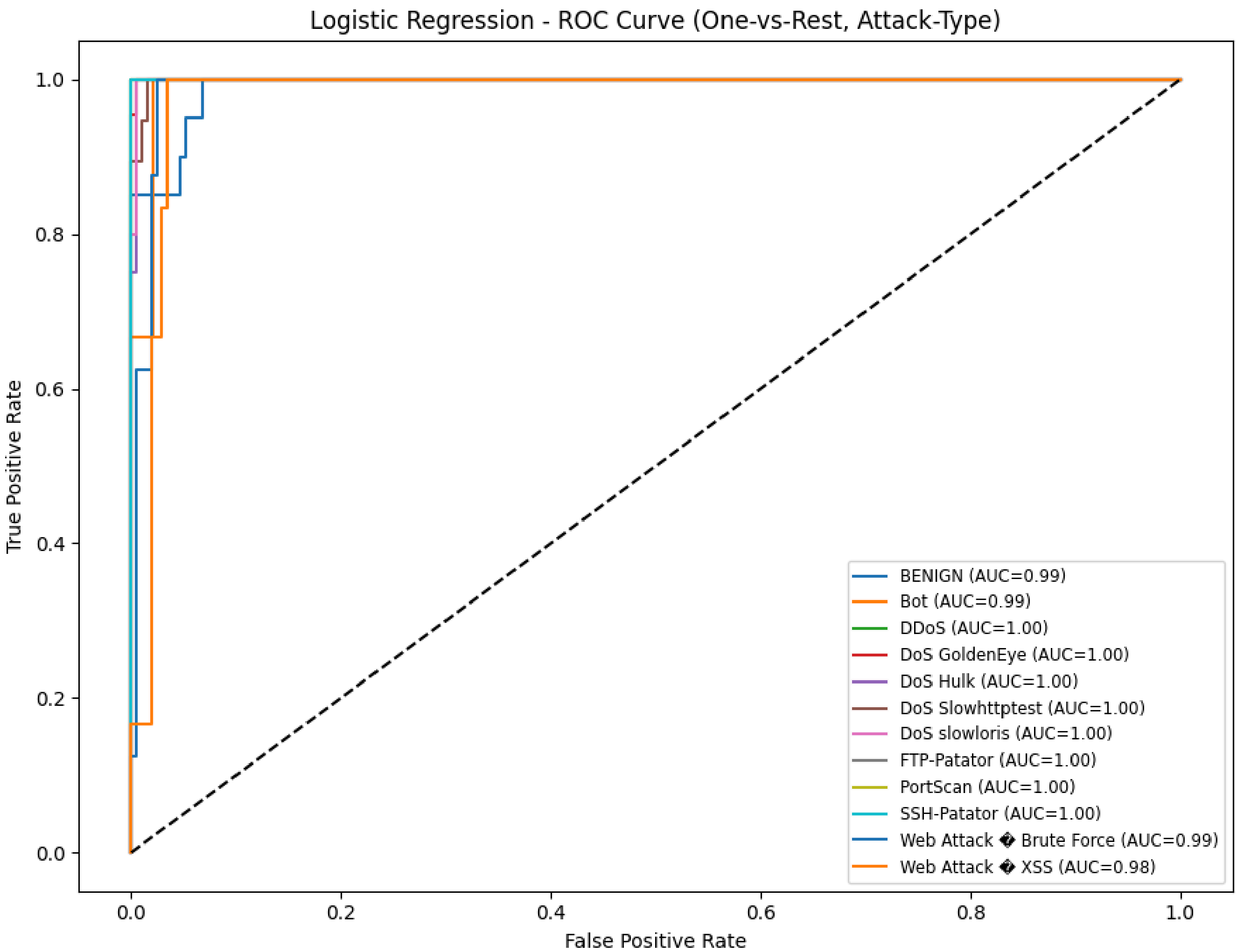


Logistic Regression (Binary) - ROC Curve
True Positive Rate (Positive label: 1)
False Positive Rate (Positive label: 1)
LogisticRegression (AUC = 0.99)
0.0
0.2
0.4
0.6
0.8
1.0

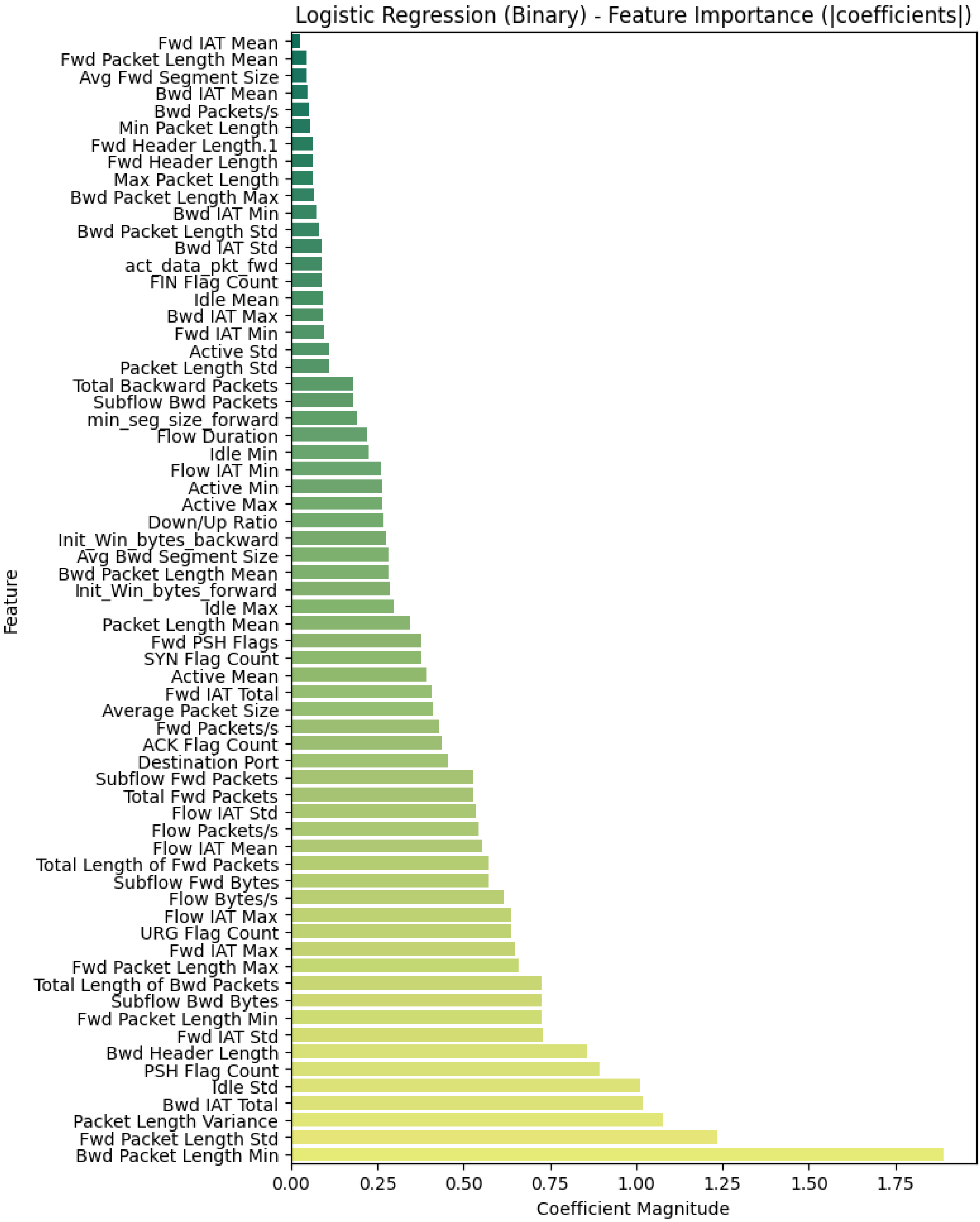
```
--- Multiclass Attack-Type classification ---
Accuracy: 0.92018779342723

Confusion Matrix (raw):
 [[17  0  1  0  1  0  0  0  1  0  0  0]
 [ 0 12  0  0  0  0  0  0  6  0  0  0]
 [ 0  0 19  0  0  0  0  0  0  0  0  0]
 [ 0  0  0 21  0  1  0  0  0  0  0  0]
 [ 0  0  0  0 19  0  0  0  1  0  0  0]
 [ 0  0  0  0  0 19  0  0  0  0  0  0]
 [ 0  0  0  0  0  0 25  0  0  0  0  0]
 [ 0  0  0  0  0  0  0 16  0  0  0  0]
 [ 0  0  0  0  0  0  0  0 16  0  0  0]
 [ 0  0  0  0  0  0  0  0  0 24  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  8  0]
 [ 0  0  0  0  0  0  0  0  0  0  6  0]]

Classification Report:
               precision    recall  f1-score   support

           0     1.0000    0.8500    0.9189        20
           1     1.0000    0.6667    0.8000        18
           2     0.9500    1.0000    0.9744        19
           3     1.0000    0.9545    0.9767        22
           4     0.9500    0.9500    0.9500        20
           5     0.9500    1.0000    0.9744        19
           6     1.0000    1.0000    1.0000        25
           7     1.0000    1.0000    1.0000        16
           9     0.6667    1.0000    0.8000        16
          10     1.0000    1.0000    1.0000        24
          11     0.5714    1.0000    0.7273         8
          13     0.0000    0.0000    0.0000         6

    accuracy                         0.9202       213
   macro avg     0.8407    0.8684    0.8435       213
weighted avg     0.9171    0.9202    0.9104       213
```



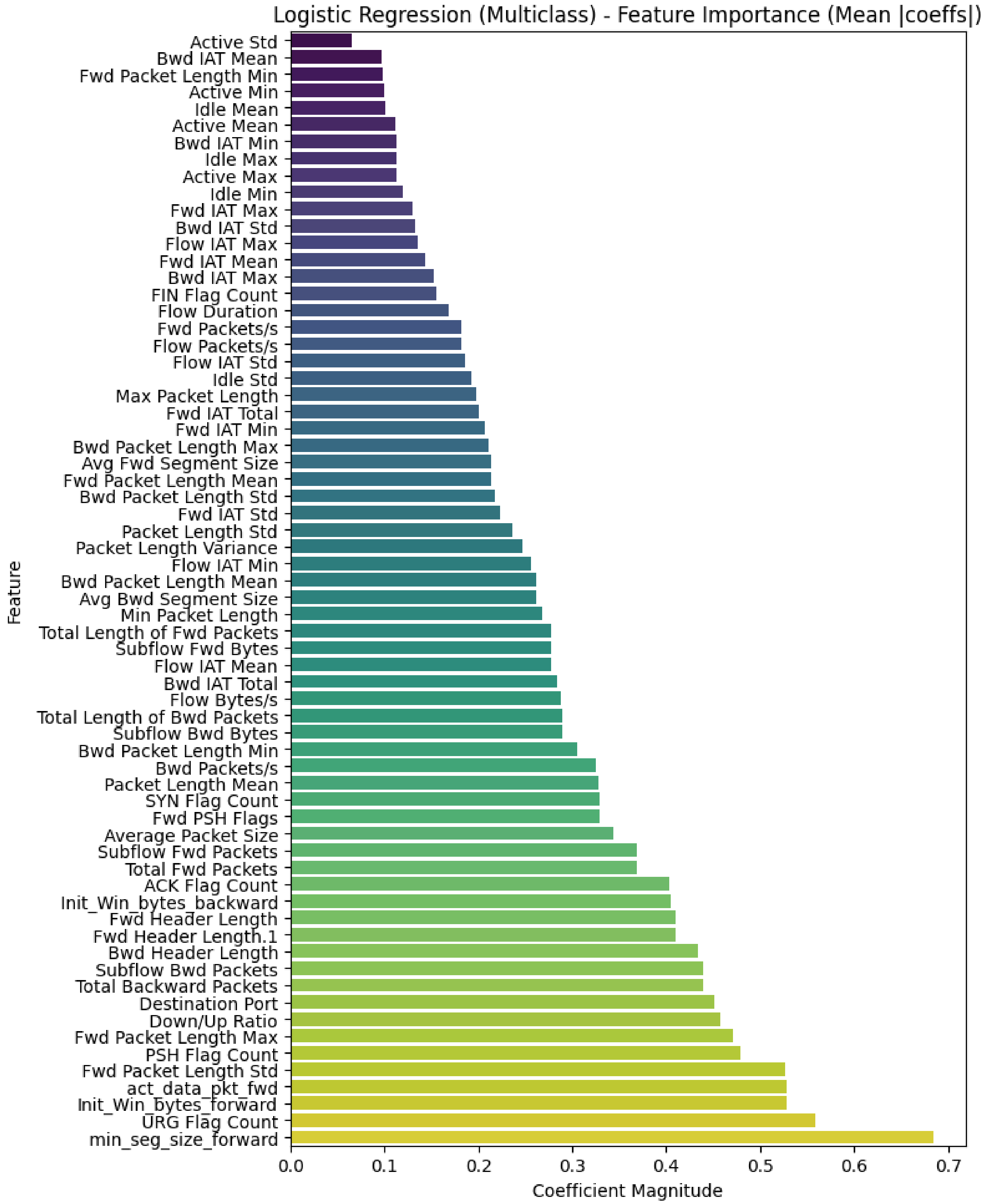

```
Multiclass detected — plotting One-vs-Rest ROC curves (robust)
Skipping class Infiltration — no positive samples in test set.
Skipping class Web Attack � Sql Injection — no positive samples in test set.
```




```
--- Feature Importance (Binary Logistic Regression) ---
```




```
--- Feature Importance (Multiclass Logistic Regression) ---
```



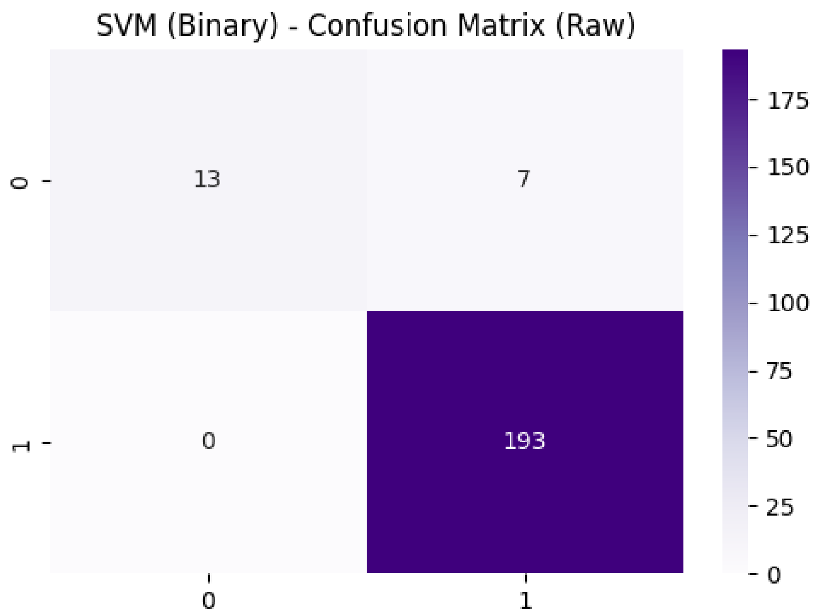
In [76]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

from sklearn.svm import SVC
from sklearn.metrics import (
    accuracy_score,
    confusion_matrix,
    classification_report,
    RocCurveDisplay,
    roc_curve,
    auc
)
from sklearn.multiclass import OneVsRestClassifier
from sklearn.preprocessing import label_binarize
```

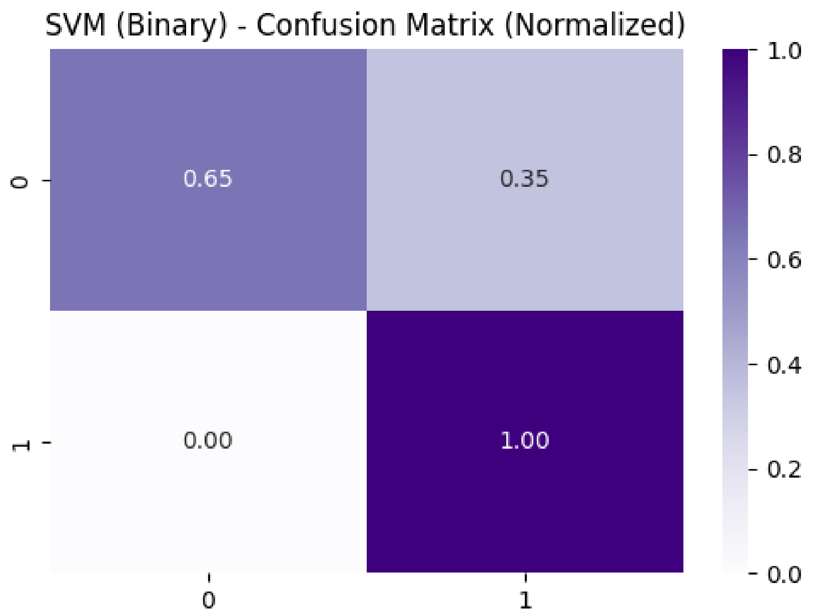
```python
from sklearn.inspection import permutation_importance


print("\n======= SVM (RBF) — BINARY + MULTICLASS =======")


# ======================================================
# 1) SVM (BINARY) — BENIGN vs ATTACK
# ======================================================
svm_binary = SVC(kernel='rbf', probability=True, random_state=42)
svm_binary.fit(X_train, y_binary_train)

pred_svm_bin = svm_binary.predict(X_test)

print("\n--- Binary SVM (BENIGN=0 / ATTACK=1) ---")
print("Accuracy:", accuracy_score(y_binary_test, pred_svm_bin))
print("\nConfusion Matrix:\n", confusion_matrix(y_binary_test, pred_svm_bin))
print("\nClassification Report:\n", classification_report(y_binary_test, pred_svm_bin, digits=4))

cm = confusion_matrix(y_binary_test, pred_svm_bin)
plt.figure(figsize=(6,4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Purples')
plt.title("SVM (Binary) - Confusion Matrix (Raw)")
plt.show()

cm_norm = confusion_matrix(y_binary_test, pred_svm_bin, normalize='true')
plt.figure(figsize=(6,4))
sns.heatmap(cm_norm, annot=True, fmt='.2f', cmap='Purples')
plt.title("SVM (Binary) - Confusion Matrix (Normalized)")
plt.show()

# ROC curve (binary)
RocCurveDisplay.from_estimator(svm_binary, X_test, y_binary_test)
plt.title("SVM (Binary) - ROC Curve")
plt.show()


# ======================================================
# 2) SVM (MULTICLASS) — ATTACK TYPE
# ======================================================
svm_multi = SVC(kernel='rbf', probability=True, random_state=42)
svm_multi.fit(X_train, y_attack_train)

pred_svm_attack = svm_multi.predict(X_test)

print("\n--- Multiclass SVM (Attack Type) ---")
print("Accuracy:", accuracy_score(y_attack_test, pred_svm_attack))
print("\nConfusion Matrix:\n", confusion_matrix(y_attack_test, pred_svm_attack))
print("\nClassification Report:\n", classification_report(y_attack_test, pred_svm_attack, digits=4))

cm = confusion_matrix(y_attack_test, pred_svm_attack)
plt.figure(figsize=(8,6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Purples')
plt.title("SVM (Multiclass) - Confusion Matrix (Raw)")
plt.show()


# ======================================================
# 3) Multiclass ROC — Robust One-vs-Rest
# ======================================================
print("\nPreparing ROC curves (robust OVR)...")

clf_ovr = OneVsRestClassifier(SVC(kernel='rbf', probability=True))
clf_ovr.fit(X_train, y_attack_train)
y_score = clf_ovr.predict_proba(X_test)
ovr_classes = clf_ovr.classes_

y_test_bin = label_binarize(y_attack_test, classes=ovr_classes)

# Fix mismatch shapes
if y_test_bin.shape[1] < y_score.shape[1]:
    pad = y_score.shape[1] - y_test_bin.shape[1]
    y_test_bin = np.hstack([y_test_bin, np.zeros((y_test_bin.shape[0], pad))])
```

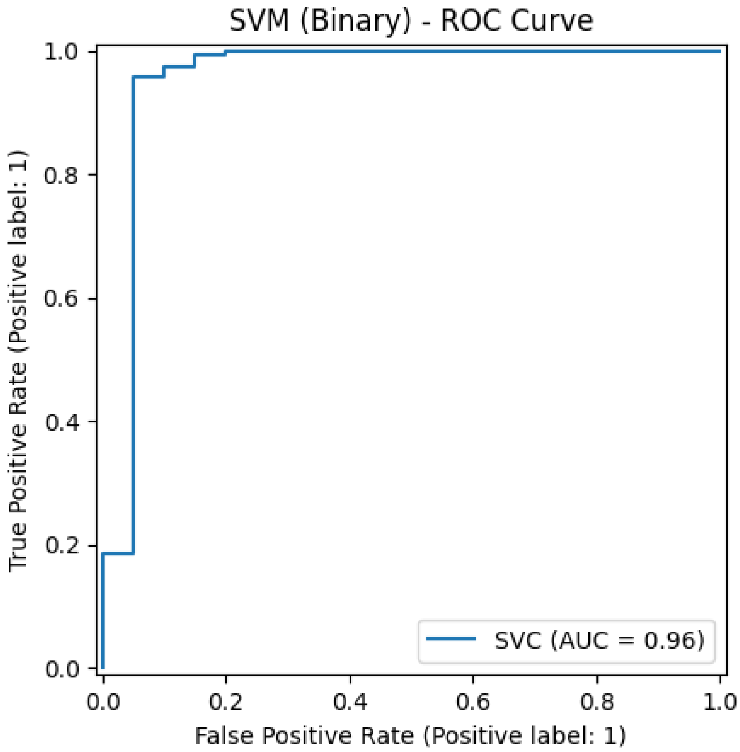
```python
elif y_test_bin.shape[1] > y_score.shape[1]:
    y_test_bin = y_test_bin[:, :y_score.shape[1]]

# human-readable class labels
use_names = False
try:
    attack_encoder
    use_names = True
except:
    pass

def class_label(i):
    if use_names:
        try:
            return attack_encoder.inverse_transform([ovr_classes[i]])[0]
        except:
            return str(ovr_classes[i])
    else:
        return str(ovr_classes[i])


plt.figure(figsize=(9, 7))
plotted_any = False

for i in range(y_score.shape[1]):
    if np.sum(y_test_bin[:, i]) == 0:
        print(f"Skipping class {class_label(i)} — no positive samples.")
        continue
    try:
        fpr, tpr, _ = roc_curve(y_test_bin[:, i], y_score[:, i])
        auc_val = auc(fpr, tpr)
        plt.plot(fpr, tpr, label=f"{class_label(i)} (AUC={auc_val:.2f})")
        plotted_any = True
    except:
        continue

if plotted_any:
    plt.plot([0,1],[0,1],'k--')
    plt.title("SVM (Multiclass) - ROC Curve (OVR)")
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.legend(fontsize='small')
    plt.tight_layout()
    plt.show()
else:
    print("No ROC curves could be plotted.")


# =======================================================
# 4) FEATURE IMPORTANCE — Permutation Importance
# =======================================================
print("\n--- Computing Feature Importance (Permutation) ---")

wrapper = svm_binary  # use binary model for importance

result = permutation_importance(
    wrapper,
    X_test,
    y_binary_test,
    n_repeats=8,
    random_state=42,
    n_jobs=-1
)

importances = result.importances_mean
sorted_idx = np.argsort(importances)

plt.figure(figsize=(8, max(6, len(sorted_idx)*0.15)))
sns.barplot(
    x=importances[sorted_idx],
    y=[feature_names[i] for i in sorted_idx],
    palette="magma"
)
```

```
plt.title("SVM (Binary) - Feature Importance (Permutation)")
plt.xlabel("Importance")
plt.ylabel("Feature")
plt.tight_layout()
plt.show()
```

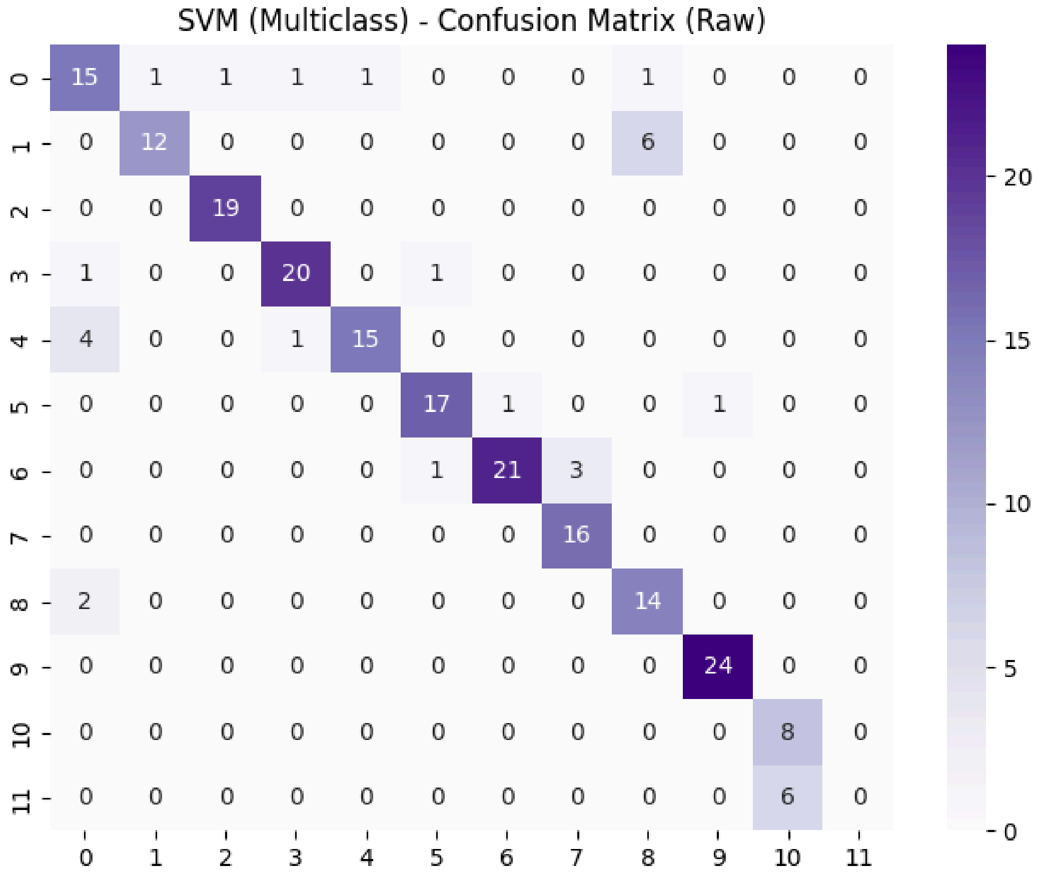
```
======= SVM (RBF) — BINARY + MULTICLASS =======

--- Binary SVM (BENIGN=0 / ATTACK=1) ---
Accuracy: 0.9671361502347418

Confusion Matrix:
 [[ 13   7]
 [  0 193]]

Classification Report:
               precision    recall  f1-score   support

           0     1.0000    0.6500    0.7879        20
           1     0.9650    1.0000    0.9822       193

    accuracy                         0.9671       213
   macro avg     0.9825    0.8250    0.8850       213
weighted avg     0.9683    0.9671    0.9639       213
```



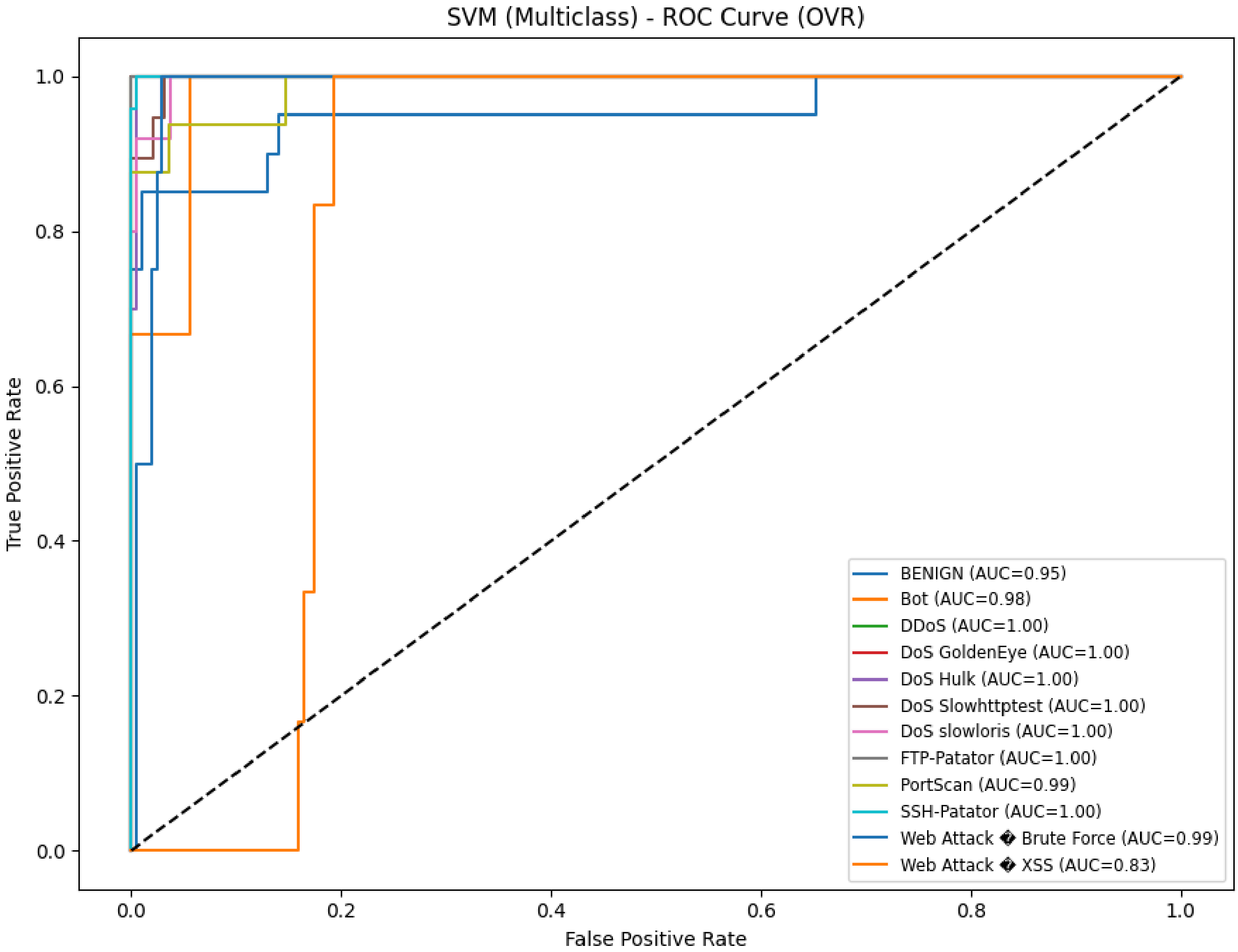




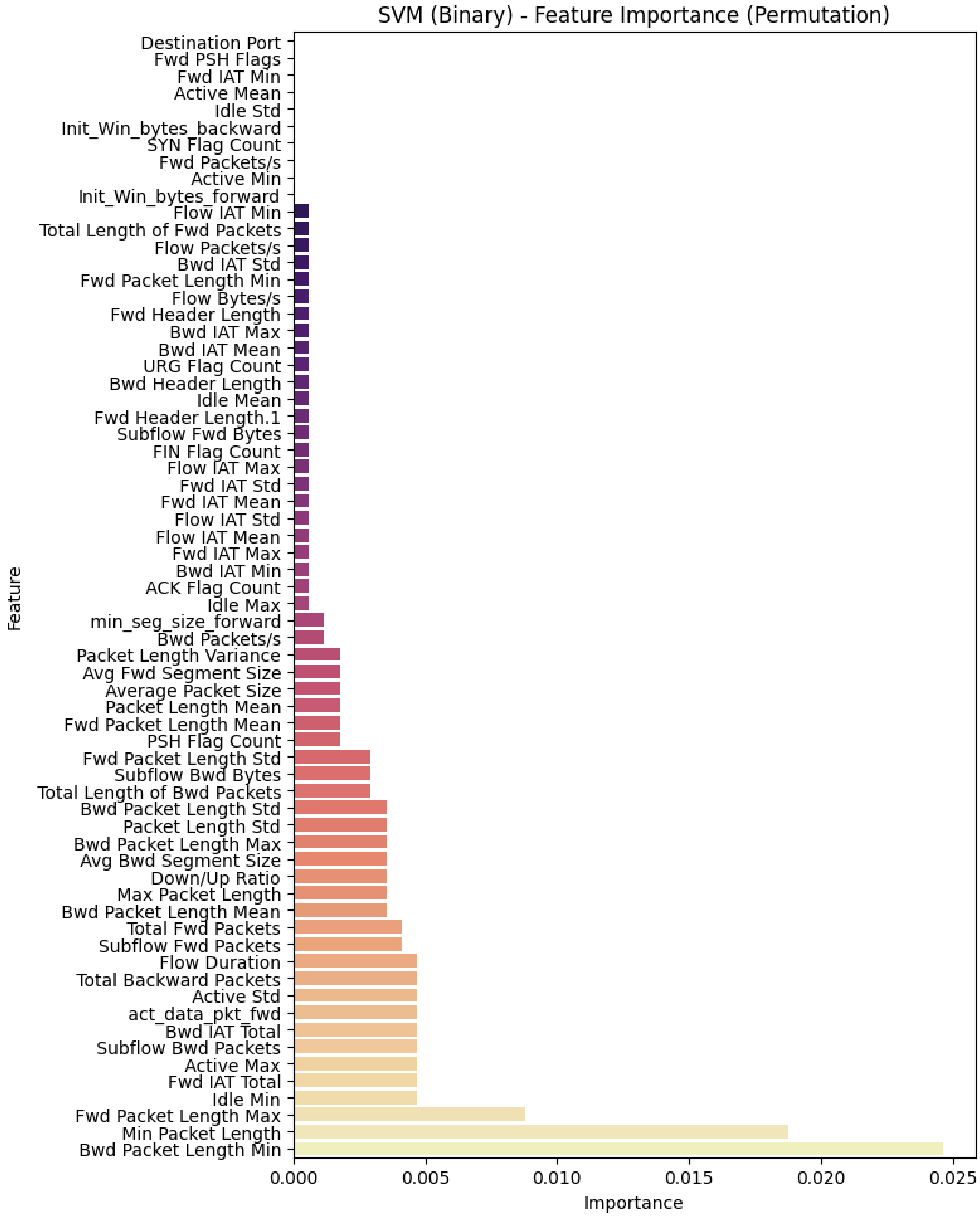

```
--- Multiclass SVM (Attack Type) ---
Accuracy: 0.8497652582159625

Confusion Matrix:
 [[15  1  1  1  1  0  0  0  1  0  0  0]
 [ 0 12  0  0  0  0  0  0  6  0  0  0]
 [ 0  0 19  0  0  0  0  0  0  0  0  0]
 [ 1  0  0 20  0  1  0  0  0  0  0  0]
 [ 4  0  0  1 15  0  0  0  0  0  0  0]
 [ 0  0  0  0  0 17  1  0  0  1  0  0]
 [ 0  0  0  0  0  1 21  3  0  0  0  0]
 [ 0  0  0  0  0  0  0 16  0  0  0  0]
 [ 2  0  0  0  0  0  0  0 14  0  0  0]
 [ 0  0  0  0  0  0  0  0  0 24  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  8  0]
 [ 0  0  0  0  0  0  0  0  0  0  6  0]]

Classification Report:
              precision    recall  f1-score   support

           0     0.6818    0.7500    0.7143        20
           1     0.9231    0.6667    0.7742        18
           2     0.9500    1.0000    0.9744        19
           3     0.9091    0.9091    0.9091        22
           4     0.9375    0.7500    0.8333        20
           5     0.8947    0.8947    0.8947        19
           6     0.9545    0.8400    0.8936        25
           7     0.8421    1.0000    0.9143        16
           9     0.6667    0.8750    0.7568        16
          10     0.9600    1.0000    0.9796        24
          11     0.5714    1.0000    0.7273         8
          13     0.0000    0.0000    0.0000         6

    accuracy                         0.8498       213
   macro avg     0.7742    0.8071    0.7810       213
weighted avg     0.8435    0.8498    0.8395       213
```




```
Preparing ROC curves (robust OVR)...
Skipping class Infiltration — no positive samples.
Skipping class Web Attack � Sql Injection — no positive samples.
```




```
--- Computing Feature Importance (Permutation) ---
```



In [79]:

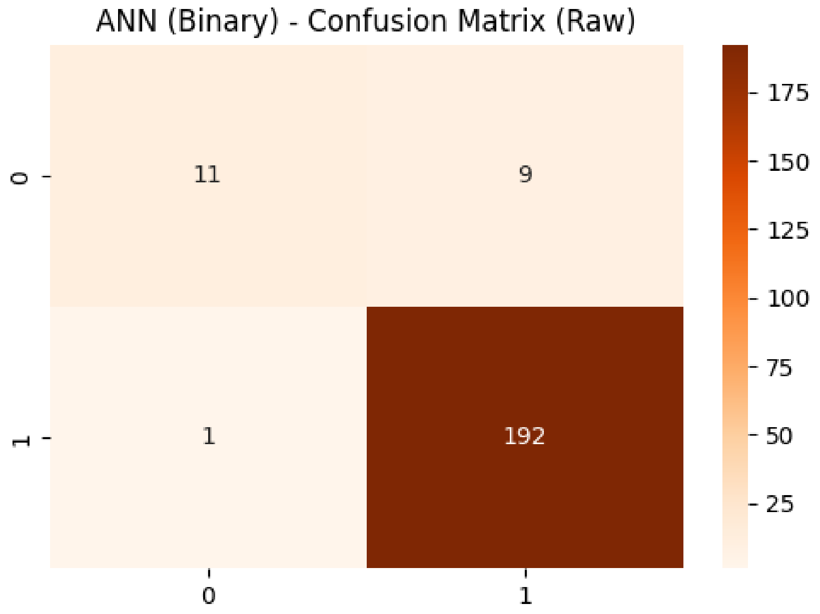
```
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

from sklearn.metrics import (
    accuracy_score,
    confusion_matrix,
    classification_report,
    roc_curve,
    auc
)
from sklearn.preprocessing import label_binarize
from sklearn.multiclass import OneVsRestClassifier
from sklearn.inspection import permutation_importance
from sklearn.base import BaseEstimator, ClassifierMixin
```

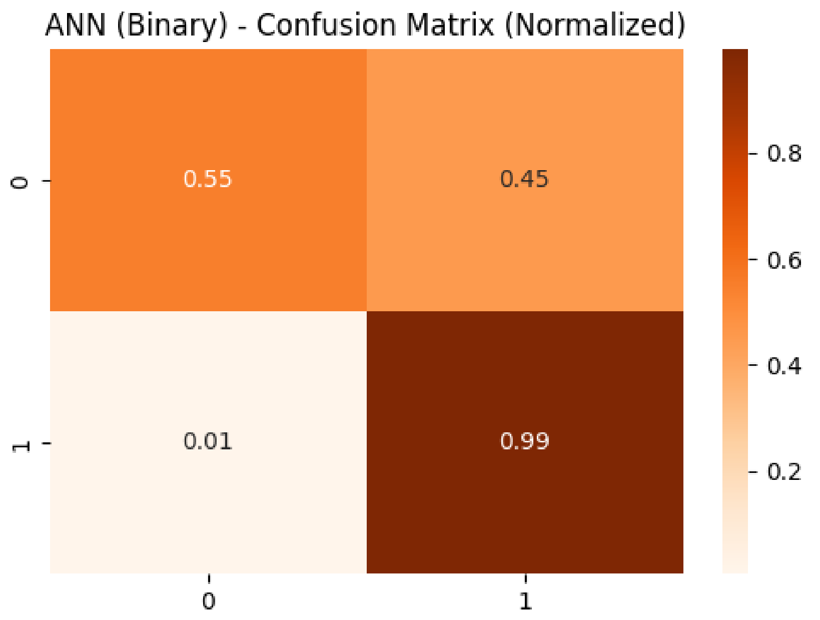
```python
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

print("\n======= ARTIFICIAL NEURAL NETWORK (ANN) =======")

# ======================================================
# 1) ANN — BINARY MODEL (BENIGN vs ATTACK)
# ======================================================
binary_model = Sequential([
    Dense(64, activation='relu', input_shape=(X_train.shape[1],)),
    Dense(32, activation='relu'),
    Dense(1, activation='sigmoid')
])

binary_model.compile(optimizer='adam',
                     loss='binary_crossentropy',
                     metrics=['accuracy'])

print("\nTraining ANN (Binary)...")
binary_model.fit(X_train, y_binary_train, epochs=10, batch_size=64, verbose=1)

# Evaluate
loss, acc = binary_model.evaluate(X_test, y_binary_test, verbose=0)
print("\nBinary ANN Accuracy:", acc)

# Predictions
pred_prob_bin = binary_model.predict(X_test).flatten()
pred_bin = (pred_prob_bin > 0.5).astype(int)

# --- Confusion Matrix (Binary)
cm = confusion_matrix(y_binary_test, pred_bin)
plt.figure(figsize=(6,4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Oranges')
plt.title("ANN (Binary) - Confusion Matrix (Raw)")
plt.show()

cm_norm = confusion_matrix(y_binary_test, pred_bin, normalize='true')
plt.figure(figsize=(6,4))
sns.heatmap(cm_norm, annot=True, fmt='.2f', cmap='Oranges')
plt.title("ANN (Binary) - Confusion Matrix (Normalized)")
plt.show()

print("\nBinary Classification Report:\n",
      classification_report(y_binary_test, pred_bin))

# ROC curve (binary)
fpr, tpr, _ = roc_curve(y_binary_test, pred_prob_bin)
plt.figure(figsize=(6,4))
plt.plot(fpr, tpr, label=f"AUC={auc(fpr,tpr):.3f}")
plt.plot([0,1], [0,1], 'k--')
plt.title("ANN (Binary) - ROC Curve")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend()
plt.show()

# ======================================================
# 2) ANN — MULTICLASS MODEL (Attack Type Classification)
# ======================================================
num_classes = len(np.unique(y_attack_train))

multiclass_model = Sequential([
    Dense(64, activation='relu', input_shape=(X_train.shape[1],)),
    Dense(32, activation='relu'),
    Dense(num_classes, activation='softmax')
])

multiclass_model.compile(optimizer='adam',
                         loss='sparse_categorical_crossentropy',
                         metrics=['accuracy'])

print("\nTraining ANN (Multiclass)...")
```

```python
multiclass_model.fit(X_train, y_attack_train, epochs=10, batch_size=64, verbose=1)

# Evaluate
loss2, acc2 = multiclass_model.evaluate(X_test, y_attack_test, verbose=0)
print("\nMulticlass ANN Accuracy:", acc2)

# Predictions
prob_multi = multiclass_model.predict(X_test)
pred_multi = np.argmax(prob_multi, axis=1)

# --- Confusion Matrix (Multiclass)
cm = confusion_matrix(y_attack_test, pred_multi)
plt.figure(figsize=(8,6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Oranges')
plt.title("ANN (Multiclass) - Confusion Matrix (Raw)")
plt.show()

print("\nMulticlass Classification Report:\n",
      classification_report(y_attack_test, pred_multi))

# =======================================================
# 3) Multiclass ROC (Robust handling for rare/missing classes)
# =======================================================
# Build class index set matching the trained output layer: 0..num_classes-1
trained_classes = np.arange(num_classes)

# Binarize y_test using the full trained_classes to ensure column alignment
y_test_bin = label_binarize(y_attack_test, classes=trained_classes)

# Defensive alignment: ensure y_test_bin and prob_multi have same number of columns
if y_test_bin.shape[1] < prob_multi.shape[1]:
    pad = prob_multi.shape[1] - y_test_bin.shape[1]
    y_test_bin = np.hstack([y_test_bin, np.zeros((y_test_bin.shape[0], pad), dtype=int)])
elif y_test_bin.shape[1] > prob_multi.shape[1]:
    y_test_bin = y_test_bin[:, :prob_multi.shape[1]]

# Prepare human-readable class labels if attack_encoder exists
use_names = False
try:
    attack_encoder  # noqa: F821
    use_names = True
except NameError:
    use_names = False

def class_label(i):
    if use_names:
        try:
            return attack_encoder.inverse_transform([i])[0]
        except Exception:
            return str(i)
    else:
        return str(i)

plt.figure(figsize=(9, 7))
plotted_any = False

# iterate over number of output columns (safe)
for i in range(prob_multi.shape[1]):
    # If no positive samples for this class in test, skip plotting
    if np.sum(y_test_bin[:, i]) == 0:
        print(f"Skipping class {class_label(i)} — no positive samples in test set.")
        continue
    try:
        fpr, tpr, _ = roc_curve(y_test_bin[:, i], prob_multi[:, i])
        auc_val = auc(fpr, tpr)
        plt.plot(fpr, tpr, label=f"{class_label(i)} (AUC={auc_val:.2f})")
        plotted_any = True
    except Exception as e:
        print(f"Could not compute ROC for class {class_label(i)}: {e}")
        continue

if plotted_any:
    plt.plot([0,1],[0,1],'k--')
```

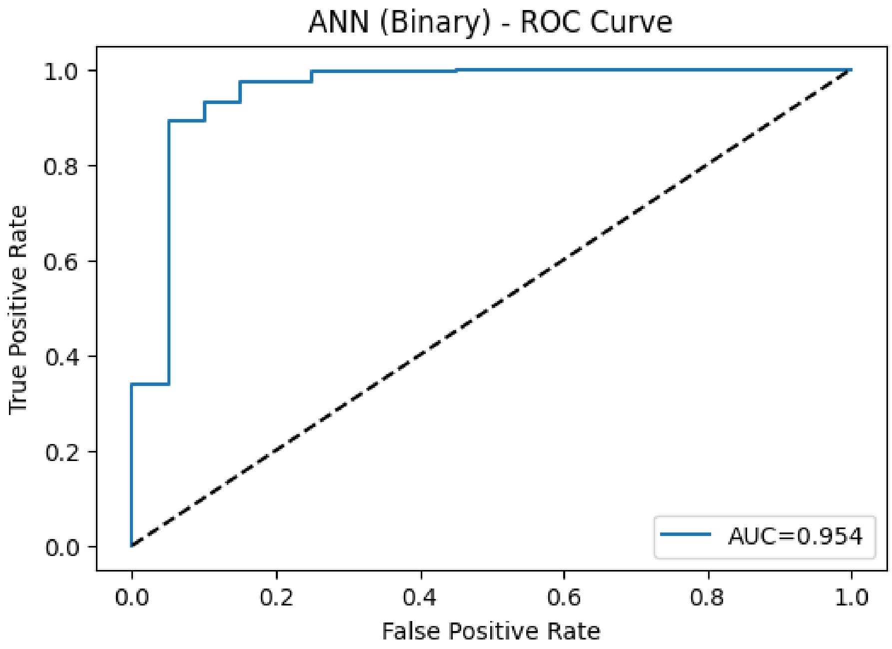
```python
    plt.title("ANN (Multiclass) - ROC Curve (OVR)")
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.legend(fontsize=8)
    plt.show()
else:
    print("No valid class ROC curves to plot (likely due to very-rare classes).")

# ======================================================
# 4) PERMUTATION FEATURE IMPORTANCE (Binary ANN)
# ======================================================
class KerasWrapper(BaseEstimator, ClassifierMixin):
    def __init__(self, model, binary=True):
        self.model = model
        self.binary = binary

    def fit(self, X, y):
        return self

    def predict(self, X):
        pred = self.model.predict(X)
        if self.binary:
            return (pred.flatten() > 0.5).astype(int)
        return np.argmax(pred, axis=1)

    def predict_proba(self, X):
        return self.model.predict(X)

print("\nComputing ANN feature importance (Permutation)...")
wrapper_bin = KerasWrapper(binary_model, binary=True)

result = permutation_importance(
    wrapper_bin,
    X_test,
    y_binary_test,
    n_repeats=8,
    random_state=42,
    n_jobs=-1
)

importances = result.importances_mean
sorted_idx = np.argsort(importances)

plt.figure(figsize=(10, max(6, len(sorted_idx)*0.15)))
sns.barplot(
    x=importances[sorted_idx],
    y=[feature_names[i] for i in sorted_idx],
    palette="magma"
)
plt.title("ANN (Binary) - Feature Importance (Permutation)")
plt.xlabel("Importance")
plt.ylabel("Feature")
plt.tight_layout()
plt.show()
```

```
======= ARTIFICIAL NEURAL NETWORK (ANN) =======

Training ANN (Binary)...
Epoch 1/10
14/14 ━━━━━━━━━━━━━━━━━━━━ 3s 8ms/step - accuracy: 0.4340 - loss: 0.8364
Epoch 2/10
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.9033 - loss: 0.4198
Epoch 3/10
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - accuracy: 0.9340 - loss: 0.2938
Epoch 4/10
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy: 0.9375 - loss: 0.2313
Epoch 5/10
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - accuracy: 0.9375 - loss: 0.1970
Epoch 6/10
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - accuracy: 0.9399 - loss: 0.1752
Epoch 7/10
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.9410 - loss: 0.1599
Epoch 8/10
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - accuracy: 0.9446 - loss: 0.1486
Epoch 9/10
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - accuracy: 0.9446 - loss: 0.1400
Epoch 10/10
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - accuracy: 0.9493 - loss: 0.1330

Binary ANN Accuracy: 0.9530516266822815
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
```

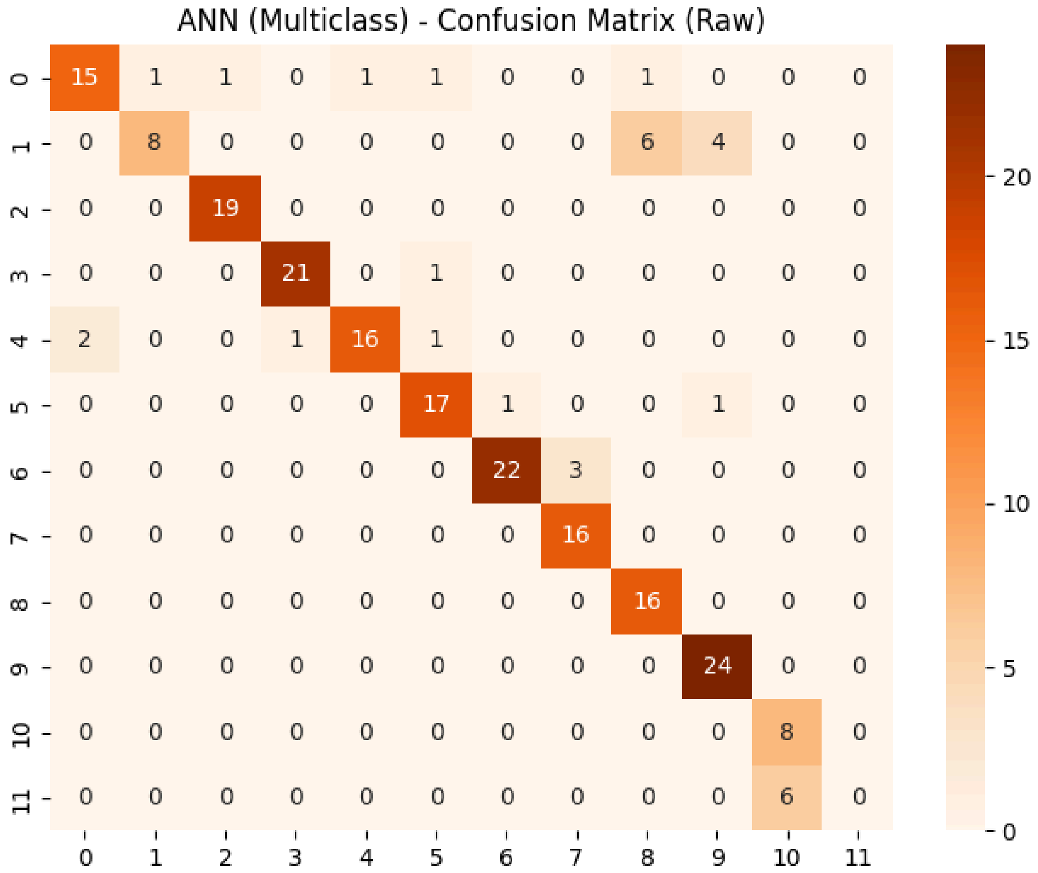




```
Binary Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.55      0.69        20
           1       0.96      0.99      0.97       193

    accuracy                           0.95       213
   macro avg       0.94      0.77      0.83       213
weighted avg       0.95      0.95      0.95       213
```



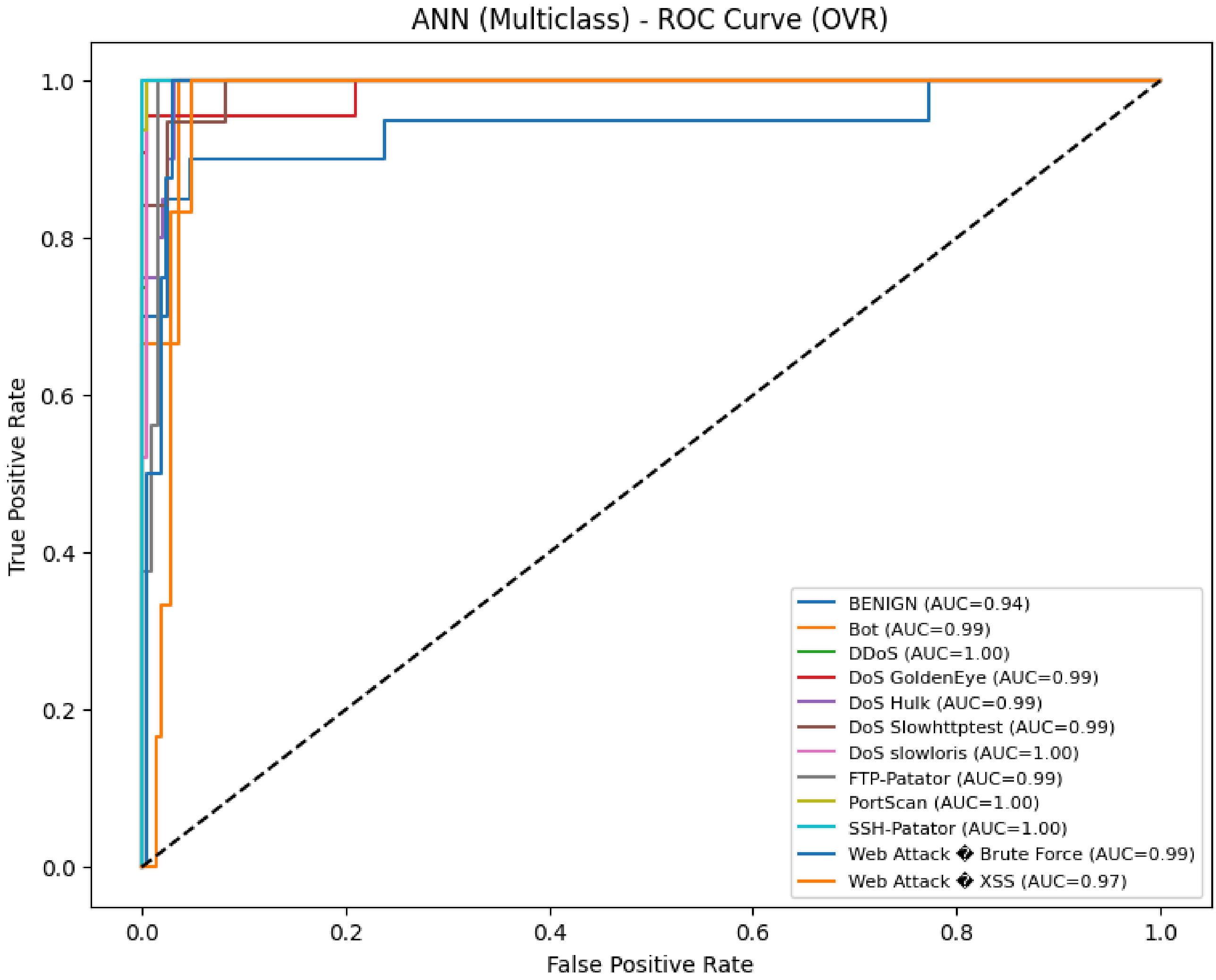

```
Training ANN (Multiclass)...
Epoch 1/10
14/14 ━━━━━━━━━━━━━━━━━━━━ 3s 9ms/step - accuracy: 0.1191 - loss: 2.6060
Epoch 2/10
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.3467 - loss: 2.1108
Epoch 3/10
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.5519 - loss: 1.7655
Epoch 4/10
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.6616 - loss: 1.4714
Epoch 5/10
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.7217 - loss: 1.2310
Epoch 6/10
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - accuracy: 0.7465 - loss: 1.0426
Epoch 7/10
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.7972 - loss: 0.8935
Epoch 8/10
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - accuracy: 0.8031 - loss: 0.7728
Epoch 9/10
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - accuracy: 0.8278 - loss: 0.6770
Epoch 10/10
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.8526 - loss: 0.6005

Multiclass ANN Accuracy: 0.8544601202011108
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step
```



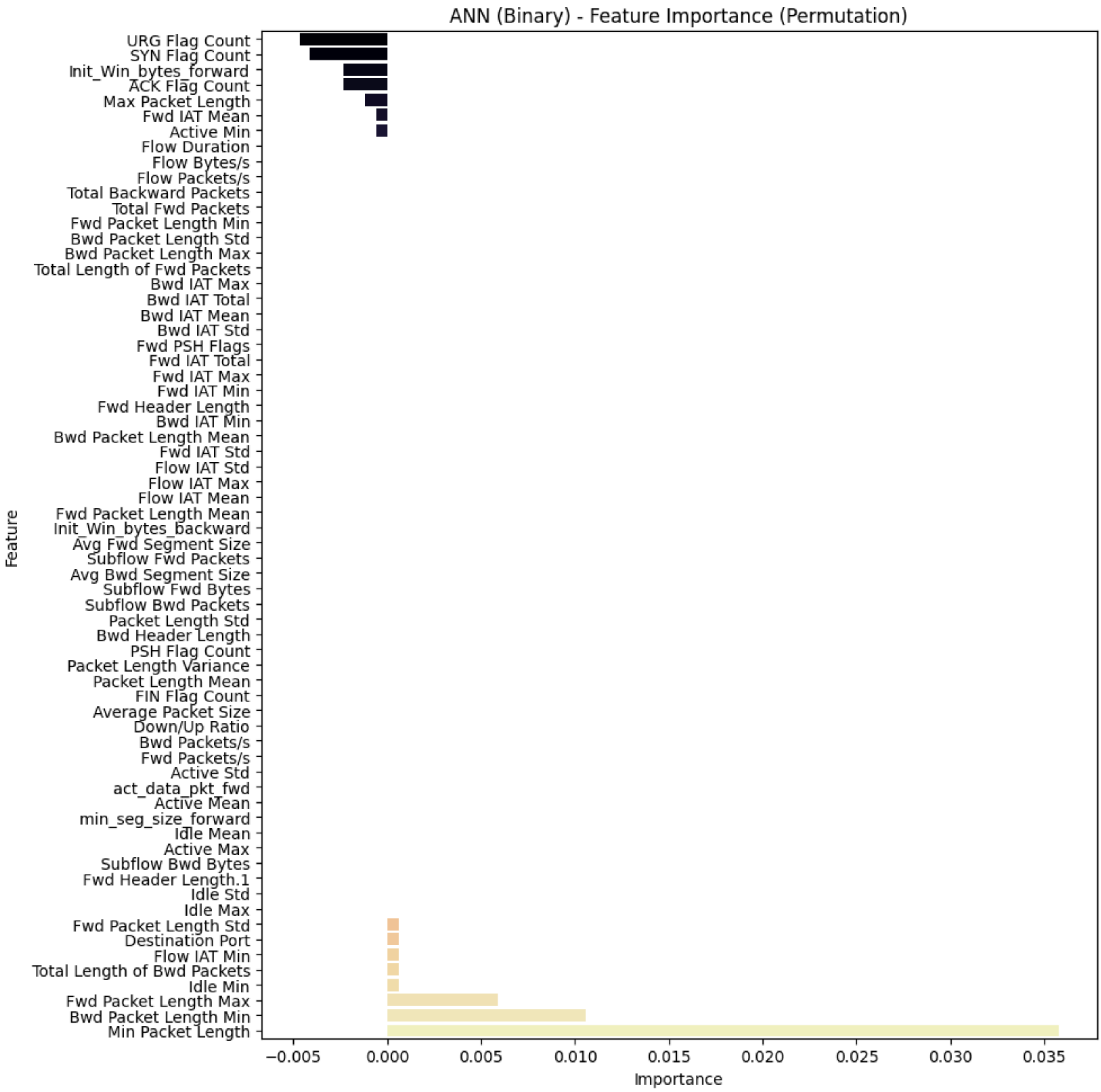
Multiclass Classification Report:

	precision	recall	f1-score	support
0	0.88	0.75	0.81	20
1	0.89	0.44	0.59	18
2	0.95	1.00	0.97	19
3	0.95	0.95	0.95	22
4	0.94	0.80	0.86	20
5	0.85	0.89	0.87	19
6	0.96	0.88	0.92	25
7	0.84	1.00	0.91	16
9	0.70	1.00	0.82	16
10	0.83	1.00	0.91	24
11	0.57	1.00	0.73	8
13	0.00	0.00	0.00	6
accuracy			0.85	213
macro avg	0.78	0.81	0.78	213
weighted avg	0.85	0.85	0.84	213

Skipping class Infiltration – no positive samples in test set.
Skipping class Web Attack � Sql Injection – no positive samples in test set.




```
Computing ANN feature importance (Permutation)...
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step
```



In [82]:
```
# === DEFAULT FEATURE BASE (DATASET MEAN VALUES) ===
default_vector = X_df.mean().values
feature_names = X_df.columns.tolist()
```

In [83]:
```
def prepare_input(user_input):
    """
    Prepares a single IDS input sample.
    - Accepts JSON (dict) or numeric list
    - Any missing features auto-filled using dataset mean
    """
    vec = default_vector.copy()

    # ----- JSON INPUT -----
    if isinstance(user_input, dict):
        for key, val in user_input.items():
            if key in feature_names:
                i = feature_names.index(key)
                vec[i] = float(val)

    # ----- LIST INPUT -----
    elif isinstance(user_input, list):
        for i, val in enumerate(user_input):
            if i < len(vec):
                vec[i] = float(val)

    else:
```

```python
        raise ValueError("Input must be JSON dict or numeric list.")

    return np.array(vec).reshape(1, -1)
```

In [91]:
```python
def run_live_demo(user_input, ensemble_mode="majority", conservative_prob=0.9):
    """
    Live demo that shows:
      - per-model binary predictions (with probs)
      - final ensemble binary decision (BENIGN / ATTACK)
      - if ATTACK -> show only the attack FAMILY (DoS, Web Attack, Brute Force, ...)
        and family-level probabilities (sum of subtype probs)
    """
    # Family mapping (subtype -> family)
    attack_family_map = {
        "BENIGN": "BENIGN",
        "DoS Hulk": "DoS",
        "DoS GoldenEye": "DoS",
        "DoS slowloris": "DoS",
        "DoS Slowhttptest": "DoS",
        "DDoS": "DDoS",
        "FTP-Patator": "Brute Force",
        "SSH-Patator": "Brute Force",
        "Web Attack – Brute Force": "Web Attack",
        "Web Attack – XSS": "Web Attack",
        "Web Attack – SQL Injection": "Web Attack",
        "PortScan": "PortScan",
        "Bot": "Botnet",
        "Infiltration": "Infiltration"
    }

    print("="*60)
    print("                LIVE IDS DEMO (4-MODEL ENSEMBLE)")
    print("="*60)

    # ---------------------------
    # 1) Prepare + scale input
    # ---------------------------
    sample = prepare_input(user_input)
    sample_scaled = scaler.transform(sample)

    # ---------------------------
    # 2) BINARY PREDICTIONS (0=benign, 1=attack)
    # ---------------------------
    results_binary = {}

    # Random Forest (binary)
    prob_rf = float(rf_binary.predict_proba(sample_scaled)[0][1])
    pred_rf = int(prob_rf > 0.5)
    results_binary["RandomForest"] = (pred_rf, prob_rf)

    # Logistic Regression (binary)
    prob_lr = float(lr_binary.predict_proba(sample_scaled)[0][1])
    pred_lr = int(prob_lr > 0.5)
    results_binary["LogisticRegression"] = (pred_lr, prob_lr)

    # SVM (binary)
    prob_svm = float(svm_binary.predict_proba(sample_scaled)[0][1])
    pred_svm = int(prob_svm > 0.5)
    results_binary["SVM (RBF)"] = (pred_svm, prob_svm)

    # ANN (binary)
    ann_prob = float(binary_model.predict(sample_scaled).flatten()[0])
    pred_ann = int(ann_prob > 0.5)
    results_binary["ANN"] = (pred_ann, ann_prob)

    # ---------------------------
    # 3) MULTICLASS PREDICTION (attack type) - raw subtype probs
    # ---------------------------
    prob_attack = multiclass_model.predict(sample_scaled)[0]   # vector length = num_subtypes
    pred_attack_idx = int(np.argmax(prob_attack))

    # Try to decode subtype name (if encoder exists)
    try:
```

```python
        subtype_names = list(attack_encoder.inverse_transform(np.arange(len(prob_attack))))
        pred_subtype_name = subtype_names[pred_attack_idx]
    except Exception:
        # fallback: use index string; we will map to generic ATTACK category
        subtype_names = [str(i) for i in range(len(prob_attack))]
        pred_subtype_name = subtype_names[pred_attack_idx]

    # ---------------------------
    # 4) MAP SUBTYPES -> FAMILY and compute family-level probs
    # ---------------------------
    family_probs = {}
    for i, subname in enumerate(subtype_names):
        family = attack_family_map.get(subname, "ATTACK")
        family_probs[family] = family_probs.get(family, 0.0) + float(prob_attack[i])

    # Choose predicted family (highest family prob)
    pred_family = max(family_probs.items(), key=lambda x: x[1])[0]
    pred_family_prob = family_probs[pred_family]

    # ---------------------------
    # 5) ENSEMBLE FINAL DECISION
    # ---------------------------
    votes = [pred_rf, pred_lr, pred_svm, pred_ann]

    if ensemble_mode == "conservative":
        # any model very confident -> attack
        if any(results_binary[m][1] >= conservative_prob for m in results_binary):
            final_pred = 1
            consensus = 'conservative_any_confident'
        else:
            final_pred = 1 if sum(votes) >= 2 else 0
            consensus = 'majority_fallback'
    else:
        final_pred = 1 if sum(votes) >= 2 else 0
        consensus = 'majority'

    final_label = "ATTACK ⚠️" if final_pred == 1 else "BENIGN 👍"
    decision_text = {0: "BENIGN 👍", 1: "ATTACK ⚠️"}

    # ---------------------------
    # 6) PRINT RESULTS (family-level for attacks)
    # ---------------------------
    print("\n--------------- MODEL OUTPUTS (BINARY) ---------------")
    for name, (pred, prob) in results_binary.items():
        print(f"{name:22s}: {pred} → {decision_text[pred]}   (P1={prob:.4f})")

    print("\n--------------- ATTACK CATEGORY (FAMILY) ---------------")
    if pred_family == "BENIGN":
        # If family mapping says BENIGN (i.e., top subtype was BENIGN)
        print("Predicted family : BENIGN")
        print(f"Family probability (BENIGN): {family_probs.get('BENIGN', 0.0):.4f}")
    else:
        print(f"Predicted family : {pred_family}")
        # Print sorted family probs (descending)
        sorted_fams = sorted(family_probs.items(), key=lambda x: x[1], reverse=True)
        for fam, p in sorted_fams:
            # hide very tiny families if you prefer, but show them for transparency
            print(f"   {fam:15s} -> {p:.4f}")

    print("\n--------------- FINAL ENSEMBLE DECISION ---------------")
    print(f"FINAL PREDICTION → {final_label}")
    print(f"Votes: {votes} (1 = attack, 0 = benign)  Consensus: {consensus}")
    print("="*60)

    # Also return a structured dict if caller wants to use it
    return {
        "per_model": results_binary,
        "family_probs": family_probs,
        "pred_family": pred_family,
        "pred_family_prob": pred_family_prob,
        "final_pred": int(final_pred),
        "final_label": final_label,
        "votes": votes,
```

```
        "consensus": consensus
    }
```

In [92]:
```python
import json
import numpy as np
from copy import deepcopy

# ---------- Subtype -> Family mapping (used for printing & family probs) ----------
attack_family_map = {
    "BENIGN": "BENIGN",
    "DoS Hulk": "DoS",
    "DoS GoldenEye": "DoS",
    "DoS slowloris": "DoS",
    "DoS Slowhttptest": "DoS",
    "DDoS": "DDoS",
    "FTP-Patator": "Brute Force",
    "SSH-Patator": "Brute Force",
    "Web Attack – Brute Force": "Web Attack",
    "Web Attack – XSS": "Web Attack",
    "Web Attack – SQL Injection": "Web Attack",
    "PortScan": "PortScan",
    "Bot": "Botnet",
    "Infiltration": "Infiltration"
}

# ---------- Helper: core prediction on an unscaled sample (1 x n_features) ----------
def _predict_from_unscaled(sample_unscaled, ensemble_mode="majority", conservative_prob=0.9):
    """
    sample_unscaled : numpy array shape (1, n_features) -> unscaled (raw)
    Returns dict with detailed outputs and MAPS subtype->family probabilities.
    """
    # scale
    sample_scaled = scaler.transform(sample_unscaled)

    # Per-model binary probs and preds
    out = {}
    # RF
    p_rf = float(rf_binary.predict_proba(sample_scaled)[0][1])
    out['RandomForest'] = {'pred': int(p_rf > 0.5), 'prob': p_rf}
    # LR
    p_lr = float(lr_binary.predict_proba(sample_scaled)[0][1])
    out['LogisticRegression'] = {'pred': int(p_lr > 0.5), 'prob': p_lr}
    # SVM
    p_svm = float(svm_binary.predict_proba(sample_scaled)[0][1])
    out['SVM'] = {'pred': int(p_svm > 0.5), 'prob': p_svm}
    # ANN (binary)
    p_ann = float(binary_model.predict(sample_scaled).flatten()[0])
    out['ANN'] = {'pred': int(p_ann > 0.5), 'prob': p_ann}

    # Multiclass attack-type prediction (from multiclass_model)
    prob_attack = multiclass_model.predict(sample_scaled)[0]  # array len = num_subtypes
    pred_attack_idx = int(np.argmax(prob_attack))

    # Resolve subtype names if encoder exists, else use indices as strings
    try:
        # attack_encoder.inverse_transform accepts array-like of encoded ints
        subtype_names = list(attack_encoder.inverse_transform(np.arange(len(prob_attack))))
        pred_subtype_name = subtype_names[pred_attack_idx]
    except Exception:
        subtype_names = [str(i) for i in range(len(prob_attack))]
        pred_subtype_name = subtype_names[pred_attack_idx]

    # Map subtype probabilities into family probabilities
    family_probs = {}
    for i, subname in enumerate(subtype_names):
        family = attack_family_map.get(subname, "ATTACK")
        family_probs[family] = family_probs.get(family, 0.0) + float(prob_attack[i])

    # Choose predicted family (highest family prob)
    pred_family = max(family_probs.items(), key=lambda x: x[1])[0]
    pred_family_prob = family_probs[pred_family]

    # Ensemble decision (binary)
```

```python
    votes = [out[m]['pred'] for m in out]
    if ensemble_mode == 'conservative':
        # any model very confident => ATTACK
        if any(out[m]['prob'] >= conservative_prob for m in out):
            final_pred = 1
            consensus = 'conservative_any_confident'
        else:
            final_pred = 1 if sum(votes) >= 2 else 0
            consensus = 'majority_fallback'
    else:
        # majority
        final_pred = 1 if sum(votes) >= 2 else 0
        consensus = 'majority'

    final_text = "ATTACK" if final_pred == 1 else "BENIGN"

    result = {
        'per_model': out,
        'multiclass': {
            'pred_index': pred_attack_idx,
            'pred_subtype_name': pred_subtype_name,
            'subtype_names': subtype_names,
            'probs': prob_attack.tolist()
        },
        'family': {
            'pred_family': pred_family,
            'pred_family_prob': float(pred_family_prob),
            'family_probs': family_probs
        },
        'ensemble': {
            'final_label': int(final_pred),
            'final_text': final_text,
            'consensus': consensus,
            'votes': votes
        }
    }
    return result

# ---------- Variant A: JSON input (string or dict) ----------
def run_live_demo_json(user_input, ensemble_mode="majority", conservative_prob=0.9, verbose=True):
    """
    Accepts:
      - JSON string (e.g. '{"Flow Duration": 100, "Total Fwd Packets": 10}')
      - Python dict {feature_name: value}
    Missing features are auto-filled using default_vector via prepare_input()
    """
    if isinstance(user_input, str):
        try:
            parsed = json.loads(user_input)
        except Exception as e:
            raise ValueError(f"Invalid JSON string: {e}")
    elif isinstance(user_input, dict):
        parsed = user_input
    else:
        raise ValueError("Input must be a JSON string or a Python dict.")

    sample_unscaled = prepare_input(parsed)  # returns 1 x n np.array
    res = _predict_from_unscaled(sample_unscaled, ensemble_mode=ensemble_mode, conservative_prob=conservativ

    if verbose:
        _print_demo_result(res)
    return res

# ---------- Variant B: List input ----------
def run_live_demo_list(num_list, ensemble_mode="majority", conservative_prob=0.9, verbose=True):
    """
    Accepts a list/tuple/ndarray of numbers (positional). Partial lists are allowed:
    the missing tail will be filled with dataset means.
    """
    if not isinstance(num_list, (list, tuple, np.ndarray)):
        raise ValueError("Input must be a list, tuple, or numpy array of numbers.")
    sample_unscaled = prepare_input(list(num_list))
    res = _predict_from_unscaled(sample_unscaled, ensemble_mode=ensemble_mode, conservative_prob=conservativ
```

```python
    if verbose:
        _print_demo_result(res)
    return res

# ---------- Variant C: Auto examples (quick demo) ----------
def run_live_demo_auto(seed=None, ensemble_mode="majority", conservative_prob=0.9, verbose=True):
    """
    Produces two auto examples:
      - benign-like: uses defaults
      - attack-like: modifies a few early features to create attack pattern
    Returns tuple (benign_result, attack_result)
    """
    rng = np.random.RandomState(seed)
    base = deepcopy(default_vector).astype(float)  # 1D array

    # benign: use defaults (maybe small random jitter)
    benign = base.copy()
    benign = benign + (rng.normal(scale=0.0, size=benign.shape))  # no jitter by default

    # attack: amplify a few early features likely to indicate DoS/flood
    attack = base.copy()

    def _get_idx_by_names(names):
        for nm in names:
            if nm in feature_names:
                return feature_names.index(nm)
        return None

    idx_fwd_pkts = _get_idx_by_names(['Total Fwd Packets', ' Total Fwd Packets', 'Total Fwd Packets '])
    idx_flow_dur = _get_idx_by_names(['Flow Duration', ' Flow Duration'])
    idx_fwd_len = _get_idx_by_names(['Total Length of Fwd Packets', ' Total Length of Fwd Packets'])
    if idx_flow_dur is None: idx_flow_dur = 1 if len(attack) > 1 else 0
    if idx_fwd_pkts is None: idx_fwd_pkts = 2 if len(attack) > 2 else 0
    if idx_fwd_len is None: idx_fwd_len = 4 if len(attack) > 4 else 0

    attack[idx_flow_dur] = max(1, attack[idx_flow_dur] * 0.2)
    attack[idx_fwd_pkts] = attack[idx_fwd_pkts] * 50 + 10
    attack[idx_fwd_len] = attack[idx_fwd_len] * 20 + 1000

    benign_sample = np.array(benign).reshape(1, -1)
    attack_sample = np.array(attack).reshape(1, -1)

    res_benign = _predict_from_unscaled(benign_sample, ensemble_mode=ensemble_mode, conservative_prob=conser
    res_attack = _predict_from_unscaled(attack_sample, ensemble_mode=ensemble_mode, conservative_prob=conser

    if verbose:
        print("\n=== AUTO-GENERATED BENIGN EXAMPLE ===")
        _print_demo_result(res_benign)
        print("\n=== AUTO-GENERATED ATTACK EXAMPLE ===")
        _print_demo_result(res_attack)

    return res_benign, res_attack

# ---------- Pretty-print helper ----------
def _print_demo_result(res):
    readable = {0: "BENIGN 👍", 1: "ATTACK ⚠️"}
    print("-"*60)
    print("Per-model binary predictions (pred, p(class=1)):")
    for m, v in res['per_model'].items():
        print(f"  {m:20s}: {v['pred']}   (p1={v['prob']:.4f})")
    print("-"*60)

    # PRINT family-level (not subtype) result
    pred_family = res['family']['pred_family']
    family_probs = res['family']['family_probs']

    print("Attack CATEGORY (family-level):")
    if pred_family == "BENIGN":
        print(f"  Predicted: BENIGN   (prob={family_probs.get('BENIGN', 0.0):.4f})")
    else:
        print(f"  Predicted family: {pred_family}   (prob={res['family']['pred_family_prob']:.4f})")
        # show top families only (hide tiny values) - top 4
```

```python
        sorted_fams = sorted(family_probs.items(), key=lambda x: x[1], reverse=True)
        for fam, p in sorted_fams[:4]:
            print(f"    {fam:15s} -> {p:.4f}")

    print("-"*60)
    print("ENSEMBLE FINAL:", res['ensemble']['final_label'], "->", res['ensemble']['final_text'])
    print("Votes:", res['ensemble']['votes'], "Consensus:", res['ensemble']['consensus'])
    print("-"*60)
```

In [95]:
```python
#1 in dataset
sample_output = run_live_demo_json({
  "Destination Port": 53,
  " Flow Duration": 204,
  " Total Fwd Packets": 2,
  " Total Backward Packets": 2,
  "Total Length of Fwd Packets": 60,
  " Total Length of Bwd Packets": 316,
  " Fwd Packet Length Max": 30,
  " Fwd Packet Length Min": 30,
  " Fwd Packet Length Mean": 30,
  " Fwd Packet Length Std": 0,
  "Bwd Packet Length Max": 158,
  " Bwd Packet Length Min": 158,
  " Bwd Packet Length Mean": 158,
  " Bwd Packet Length Std": 0,
  "Flow Bytes/s": 1843137.255,
  " Flow Packets/s": 19607.84314,
  " Flow IAT Mean": 68,
  " Flow IAT Std": 112.5833025,
  " Flow IAT Max": 198,
  " Flow IAT Min": 3,
  "Fwd IAT Total": 3,
  " Fwd IAT Mean": 3,
  " Fwd IAT Std": 0,
  " Fwd IAT Max": 3,
  " Fwd IAT Min": 3,
  "Bwd IAT Total": 3,
  " Bwd IAT Mean": 3,
  " Bwd IAT Std": 0,
  " Bwd IAT Max": 3,
  " Bwd IAT Min": 3,
  "Fwd PSH Flags": 0,
  " Bwd PSH Flags": 0,
  " Fwd URG Flags": 0,
  " Bwd URG Flags": 0,
  " Fwd Header Length": 64,
  " Bwd Header Length": 64,
  "Fwd Packets/s": 9803.921569,
  " Bwd Packets/s": 9803.921569,
  " Min Packet Length": 30,
  " Max Packet Length": 158,
  " Packet Length Mean": 81.2,
  " Packet Length Std": 70.10848736,
  " Packet Length Variance": 4915.2,
  "FIN Flag Count": 0,
  " SYN Flag Count": 0,
  " RST Flag Count": 0,
  " PSH Flag Count": 0,
  " ACK Flag Count": 0,
  " URG Flag Count": 0,
  " CWE Flag Count": 0,
  " ECE Flag Count": 0,
  " Down/Up Ratio": 1,
  " Average Packet Size": 101.5,
  " Avg Fwd Segment Size": 30,
  " Avg Bwd Segment Size": 158,
  " Fwd Header Length.1": 64,
  "Fwd Avg Bytes/Bulk": 0,
  " Fwd Avg Packets/Bulk": 0,
  " Fwd Avg Bulk Rate": 0,
  " Bwd Avg Bytes/Bulk": 0,
  " Bwd Avg Packets/Bulk": 0,
  "Bwd Avg Bulk Rate": 0,
```

```
  "Subflow Fwd Packets": 2,
  " Subflow Fwd Bytes": 60,
  " Subflow Bwd Packets": 2,
  " Subflow Bwd Bytes": 316,
  "Init_Win_bytes_forward": -1,
  " Init_Win_bytes_backward": -1,
  " act_data_pkt_fwd": 1,
  " min_seg_size_forward": 32,
  "Active Mean": 0,
  " Active Std": 0,
  " Active Max": 0,
  " Active Min": 0,
  "Idle Mean": 0,
  " Idle Std": 0,
  " Idle Max": 0,
  " Idle Min": 0
})
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 36ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 37ms/step
------------------------------------------------------------
Per-model binary predictions (pred, p(class=1)):
  RandomForest        : 0   (p1=0.0150)
  LogisticRegression  : 0   (p1=0.0000)
  SVM                 : 0   (p1=0.0000)
  ANN                 : 0   (p1=0.0303)
------------------------------------------------------------
Attack CATEGORY (family-level):
  Predicted: BENIGN   (prob=0.9882)
------------------------------------------------------------
ENSEMBLE FINAL: 0 -> BENIGN
Votes: [0, 0, 0, 0] Consensus: majority
------------------------------------------------------------
```

In [97]:

```
#250 in dataset
sample_output = run_live_demo_json(
  {
  "Destination Port": 80,
  " Flow Duration": 20998592,
  " Total Fwd Packets": 2,
  " Total Backward Packets": 1,
  "Total Length of Fwd Packets": 13,
  " Total Length of Bwd Packets": 0,
  " Fwd Packet Length Max": 13,
  " Fwd Packet Length Min": 0,
  " Fwd Packet Length Mean": 6.5,
  " Fwd Packet Length Std": 9.192388155,
  "Bwd Packet Length Max": 0,
  " Bwd Packet Length Min": 0,
  " Bwd Packet Length Mean": 0,
  " Bwd Packet Length Std": 0,
  "Flow Bytes/s": 0.619089127,
  " Flow Packets/s": 0.142866722,
  " Flow IAT Mean": 10500000,
  " Flow IAT Std": 14800000,
  " Flow IAT Max": 21000000,
  " Flow IAT Min": 65,
  "Fwd IAT Total": 21000000,
  " Fwd IAT Mean": 21000000,
  " Fwd IAT Std": 0,
  " Fwd IAT Max": 21000000,
  " Fwd IAT Min": 21000000,
  "Bwd IAT Total": 0,
  " Bwd IAT Mean": 0,
  " Bwd IAT Std": 0,
  " Bwd IAT Max": 0,
  " Bwd IAT Min": 0,
  "Fwd PSH Flags": 1,
  " Bwd PSH Flags": 0,
  " Fwd URG Flags": 0,
  " Bwd URG Flags": 0,
  " Fwd Header Length": 64,
  " Bwd Header Length": 32,
  "Fwd Packets/s": 0.095244481,
```

```
  " Bwd Packets/s": 0.047622241,
  " Min Packet Length": 0,
  " Max Packet Length": 13,
  " Packet Length Mean": 6.5,
  " Packet Length Std": 7.505553499,
  " Packet Length Variance": 56.33333333,
  "FIN Flag Count": 0,
  " SYN Flag Count": 1,
  " RST Flag Count": 0,
  " PSH Flag Count": 0,
  " ACK Flag Count": 1,
  " URG Flag Count": 0,
  " CWE Flag Count": 0,
  " ECE Flag Count": 0,
  " Down/Up Ratio": 0,
  " Average Packet Size": 8.666666667,
  " Avg Fwd Segment Size": 6.5,
  " Avg Bwd Segment Size": 0,
  " Fwd Header Length.1": 64,
  "Fwd Avg Bytes/Bulk": 0,
  " Fwd Avg Packets/Bulk": 0,
  " Fwd Avg Bulk Rate": 0,
  " Bwd Avg Bytes/Bulk": 0,
  " Bwd Avg Packets/Bulk": 0,
  "Bwd Avg Bulk Rate": 0,
  "Subflow Fwd Packets": 2,
  " Subflow Fwd Bytes": 13,
  " Subflow Bwd Packets": 1,
  " Subflow Bwd Bytes": 0,
  "Init_Win_bytes_forward": 229,
  " Init_Win_bytes_backward": 235,
  " act_data_pkt_fwd": 0,
  " min_seg_size_forward": 32,
  "Active Mean": 0,
  " Active Std": 0,
  " Active Max": 0,
  " Active Min": 0,
  "Idle Mean": 0,
  " Idle Std": 0,
  " Idle Max": 0,
  " Idle Min": 0
}

 )
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 36ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
------------------------------------------------------------
Per-model binary predictions (pred, p(class=1)):
  RandomForest        : 1   (p1=0.8000)
  LogisticRegression  : 1   (p1=0.9967)
  SVM                 : 1   (p1=0.9417)
  ANN                 : 1   (p1=0.9693)
------------------------------------------------------------
Attack CATEGORY (family-level):
  Predicted family: DoS   (prob=0.6359)
    DoS             -> 0.6359
    Brute Force     -> 0.2878
    ATTACK          -> 0.0348
    BENIGN          -> 0.0255
------------------------------------------------------------
ENSEMBLE FINAL: 1 -> ATTACK
Votes: [1, 1, 1, 1] Consensus: majority
------------------------------------------------------------
```

In [104…

```
#1062 in dataset
sample_output = run_live_demo_json(
{
  "Destination Port": 3389,
  " Flow Duration": 24,
  " Total Fwd Packets": 1,
  " Total Backward Packets": 1,
  "Total Length of Fwd Packets": 2,
  " Total Length of Bwd Packets": 6,
```

```
" Fwd Packet Length Max": 2,
" Fwd Packet Length Min": 2,
" Fwd Packet Length Mean": 2,
" Fwd Packet Length Std": 0,
"Bwd Packet Length Max": 6,
" Bwd Packet Length Min": 6,
" Bwd Packet Length Mean": 6,
" Bwd Packet Length Std": 0,
"Flow Bytes/s": 333333.3333,
" Flow Packets/s": 83333.33333,
" Flow IAT Mean": 24,
" Flow IAT Std": 0,
" Flow IAT Max": 24,
" Flow IAT Min": 24,
"Fwd IAT Total": 0,
" Fwd IAT Mean": 0,
" Fwd IAT Std": 0,
" Fwd IAT Max": 0,
" Fwd IAT Min": 0,
"Bwd IAT Total": 0,
" Bwd IAT Mean": 0,
" Bwd IAT Std": 0,
" Bwd IAT Max": 0,
" Bwd IAT Min": 0,
"Fwd PSH Flags": 0,
" Bwd PSH Flags": 0,
" Fwd URG Flags": 0,
" Bwd URG Flags": 0,
" Fwd Header Length": 24,
" Bwd Header Length": 20,
"Fwd Packets/s": 41666.66667,
" Bwd Packets/s": 41666.66667,
" Min Packet Length": 2,
" Max Packet Length": 6,
" Packet Length Mean": 3.333333333,
" Packet Length Std": 2.309401077,
" Packet Length Variance": 5.333333333,
"FIN Flag Count": 0,
" SYN Flag Count": 0,
" RST Flag Count": 0,
" PSH Flag Count": 1,
" ACK Flag Count": 0,
" URG Flag Count": 0,
" CWE Flag Count": 0,
" ECE Flag Count": 0,
" Down/Up Ratio": 1,
" Average Packet Size": 5,
" Avg Fwd Segment Size": 2,
" Avg Bwd Segment Size": 6,
" Fwd Header Length.1": 24,
"Fwd Avg Bytes/Bulk": 0,
" Fwd Avg Packets/Bulk": 0,
" Fwd Avg Bulk Rate": 0,
" Bwd Avg Bytes/Bulk": 0,
" Bwd Avg Packets/Bulk": 0,
"Bwd Avg Bulk Rate": 0,
"Subflow Fwd Packets": 1,
" Subflow Fwd Bytes": 2,
" Subflow Bwd Packets": 1,
" Subflow Bwd Bytes": 6,
"Init_Win_bytes_forward": 1024,
" Init_Win_bytes_backward": 0,
" act_data_pkt_fwd": 0,
" min_seg_size_forward": 24,
"Active Mean": 0,
" Active Std": 0,
" Active Max": 0,
" Active Min": 0,
"Idle Mean": 0,
" Idle Std": 0,
" Idle Max": 0,
" Idle Min": 0
```

```
}
)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 139ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 104ms/step
------------------------------------------------------------
Per-model binary predictions (pred, p(class=1)):
  RandomForest        : 1   (p1=1.0000)
  LogisticRegression  : 1   (p1=0.9660)
  SVM                 : 1   (p1=0.9521)
  ANN                 : 1   (p1=0.9409)
------------------------------------------------------------
Attack CATEGORY (family-level):
  Predicted family: PortScan   (prob=0.7985)
    PortScan        -> 0.7985
    Botnet          -> 0.0764
    BENIGN          -> 0.0539
    Brute Force     -> 0.0344
------------------------------------------------------------
ENSEMBLE FINAL: 1 -> ATTACK
Votes: [1, 1, 1, 1] Consensus: majority
------------------------------------------------------------
```

In [ ]: