CYBERML Project 2025-2026

IoT Intrusion Detection and Attack Analysis

Objectives:

1. **Classification and Anomaly Detection** for tracking attacks
2. **Adversarial Attacks** against classification (bonus)

Dataset: CIC IoT-DIAD 2024

Source: https://www.unb.ca/cic/datasets/iot-diad-2024.html

Note: This notebook uses stratified sampling to handle the large 50GB dataset efficiently.

1. Environment Setup and Dependencies

In [335…
```
# Install required packages
import sys
!{sys.executable} -m pip install pandas numpy scikit-learn matplotlib sea
```

```
/home/regium/Documents/EPITA/CYBER/cyberml/.venv/bin/python: No module nam
ed pip
```

In [336…
```
# Download http://cicresearch.ca/IOTDataset/CIC%20IoT-IDAD%20Dataset%2020
# Download the full directory recursively using wget under data/
# !wget -r -np -nH --cut-dirs=3 -R "index.html*" -P data/ "http://cicrese
```

In [337…
```
# Import required libraries
import os
import torch
import glob
import warnings
import gc
warnings.filterwarnings('ignore')

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Set matplotlib style
plt.style.use('seaborn-v0_8-whitegrid')
plt.rcParams['figure.figsize'] = (12, 6)
plt.rcParams['font.size'] = 10

# Preprocessing
from sklearn.preprocessing import StandardScaler, LabelEncoder, MinMaxSca
from sklearn.model_selection import train_test_split, cross_val_score, St
from sklearn.utils import shuffle
```

```python
# Unsupervised Learning (Anomaly Detection)
from sklearn.ensemble import IsolationForest
from sklearn.neighbors import LocalOutlierFactor
from sklearn.svm import OneClassSVM

# Supervised Learning (Classification)
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClas
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier

# Metrics
from sklearn.metrics import (
    confusion_matrix, classification_report, accuracy_score,
    precision_score, recall_score, f1_score, roc_auc_score,
    average_precision_score, balanced_accuracy_score, matthews_corrcoef,
    precision_recall_curve, roc_curve, ConfusionMatrixDisplay
)

# Imbalanced data handling
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler
from imblearn.pipeline import Pipeline as ImbPipeline

# Set random seed for reproducibility
RANDOM_STATE = 42
np.random.seed(RANDOM_STATE)

print("All libraries imported successfully!")
```

```
All libraries imported successfully!
```

2. Memory-Efficient Data Loading with Stratified Sampling

Since the dataset is ~50GB, we use stratified sampling to:

- Sample a fixed number of rows from each attack category
- Maintain class distribution representation
- Keep memory usage manageable

In [338…

```python
# Configuration for sampling
DATA_ROOT = "data/Anomaly Detection - Flow Based features/"
SAMPLES_PER_CATEGORY = 10000  # Adjust based on available memory
CHUNK_SIZE = 50000  # Read CSV in chunks

# Define attack categories and their folder mappings
ATTACK_CATEGORIES = {
    'Benign': 'Benign',
    'BruteForce': 'BruteForce',
    'DDoS': 'DDoS',
    'DoS': 'DoS',
    'Mirai': 'Mirai',
    'Recon': 'Recon',
```

```
    'Spoofing': 'Spoofing',
    'Web-Based': 'Web-Based'
}

print(f"Sampling {SAMPLES_PER_CATEGORY} rows per category")
print(f"Categories: {list(ATTACK_CATEGORIES.keys())}")
```

```
Sampling 10000 rows per category
Categories: ['Benign', 'BruteForce', 'DDoS', 'DoS', 'Mirai', 'Recon', 'Spo
ofing', 'Web-Based']
```

In [339…

```
def get_csv_files_for_category(category_path):
    """Recursively find all CSV files in a category folder."""
    csv_files = glob.glob(os.path.join(category_path, "**/*.csv"), recurs
    return csv_files

def sample_from_csv(file_path, n_samples, chunk_size=CHUNK_SIZE):
    """Sample n rows from a CSV file using reservoir sampling approach.""
    # First, count total rows (fast scan)
    total_rows = sum(1 for _ in open(file_path, 'r')) - 1  # -1 for heade

    if total_rows <= 0:
        return None

    if total_rows <= n_samples:
        # File is small enough, read entirely
        try:
            return pd.read_csv(file_path, low_memory=False)
        except Exception as e:
            print(f"Error reading {file_path}: {e}")
            return None

    # Random sample of row indices to keep
    skip_idx = set(range(1, total_rows + 1)) - set(np.random.choice(range

    try:
        df = pd.read_csv(file_path, skiprows=skip_idx, low_memory=False)
        return df
    except Exception as e:
        print(f"Error sampling {file_path}: {e}")
        return None

def load_category_sample(category_name, category_folder, n_samples):
    """Load a stratified sample from all files in a category."""
    category_path = os.path.join(DATA_ROOT, category_folder)
    csv_files = get_csv_files_for_category(category_path)

    if not csv_files:
        print(f"No CSV files found in {category_path}")
        return None

    print(f"\n{category_name}: Found {len(csv_files)} CSV files")

    # Distribute samples across files
    samples_per_file = max(1, n_samples // len(csv_files))

    dfs = []
    total_sampled = 0

    for csv_file in csv_files:
```

```
        if total_sampled >= n_samples:
            break

        remaining = n_samples - total_sampled
        to_sample = min(samples_per_file, remaining)

        df_sample = sample_from_csv(csv_file, to_sample)
        if df_sample is not None and len(df_sample) > 0:
            dfs.append(df_sample)
            total_sampled += len(df_sample)
            print(f"  - {os.path.basename(csv_file)}: {len(df_sample)} sa

    if not dfs:
        return None

    result = pd.concat(dfs, ignore_index=True)
    result['Label'] = category_name

    # Clean up
    del dfs
    gc.collect()

    print(f"  Total samples for {category_name}: {len(result)}")
    return result
```

In [340…

```
# Load stratified samples from each category
print("Loading stratified samples from each attack category...")
print("="*60)

all_samples = []

for category_name, category_folder in ATTACK_CATEGORIES.items():
    df_category = load_category_sample(category_name, category_folder, SA
    if df_category is not None:
        all_samples.append(df_category)
    gc.collect()

# Combine all samples
df = pd.concat(all_samples, ignore_index=True)
del all_samples
gc.collect()

print("\n" + "="*60)
print(f"Total dataset shape: {df.shape}")
print(f"Memory usage: {df.memory_usage(deep=True).sum() / 1024**2:.2f} MB
```

```
Loading stratified samples from each attack category...
============================================================

Benign: Found 4 CSV files
  - BenignTraffic3.pcap_Flow.csv: 2500 samples
  - BenignTraffic1.pcap_Flow.csv: 2500 samples
  - BenignTraffic.pcap_Flow.csv: 2500 samples
  - BenignTraffic2.pcap_Flow.csv: 2500 samples
  Total samples for Benign: 10000

BruteForce: Found 1 CSV files
  - DictionaryBruteForce.pcap_Flow.csv: 3619 samples
  Total samples for BruteForce: 3619

DDoS: Found 61 CSV files
  - DDoS-HTTP_Flood-.pcap_Flow.csv: 163 samples
  - DDoS-ACK_Fragmentation7.pcap_Flow.csv: 163 samples
  - DDoS-ACK_Fragmentation.pcap_Flow.csv: 163 samples
  - DDoS-ACK_Fragmentation9.pcap_Flow.csv: 163 samples
  - DDoS-ACK_Fragmentation8.pcap_Flow.csv: 163 samples
  - DDoS-ACK_Fragmentation6.pcap_Flow.csv: 163 samples
  - DDoS-ACK_Fragmentation5.pcap_Flow.csv: 163 samples
  - DDoS-ACK_Fragmentation11.pcap_Flow.csv: 163 samples
  - DDoS-ACK_Fragmentation10.pcap_Flow.csv: 163 samples
  - DDoS-ACK_Fragmentation3.pcap_Flow.csv: 163 samples
  - DDoS-ACK_Fragmentation4.pcap_Flow.csv: 163 samples
  - DDoS-ACK_Fragmentation1.pcap_Flow.csv: 163 samples
  - DDoS-ACK_Fragmentation12.pcap_Flow.csv: 163 samples
  - DDoS-ACK_Fragmentation2.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood4.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood10.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood25.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood22.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood19.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood23.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood5.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood21.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood6.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood1.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood14.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood24.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood8.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood16.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood15.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood18.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood12.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood7.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood26.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood20.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood13.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood11.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood9.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood3.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood17.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Flood2.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Fragmentation12.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Fragmentation2.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Fragmentation8.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Fragmentation.pcap_Flow.csv: 163 samples
```

```
  - DDoS-ICMP_Fragmentation9.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Fragmentation18.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Fragmentation15.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Fragmentation1.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Fragmentation16.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Fragmentation10.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Fragmentation5.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Fragmentation19.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Fragmentation11.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Fragmentation17.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Fragmentation4.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Fragmentation14.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Fragmentation3.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Fragmentation7.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Fragmentation6.pcap_Flow.csv: 163 samples
  - DDoS-ICMP_Fragmentation13.pcap_Flow.csv: 163 samples
  Total samples for DDoS: 9943

DoS: Found 30 CSV files
  - DoS-UDP_Flood16.pcap_Flow.csv: 333 samples
  - DoS-UDP_Flood4.pcap_Flow.csv: 333 samples
  - DoS-UDP_Flood11.pcap_Flow.csv: 333 samples
  - DoS-UDP_Flood.pcap_Flow.csv: 333 samples
  - DoS-UDP_Flood3.pcap_Flow.csv: 333 samples
  - DoS-UDP_Flood5.pcap_Flow.csv: 333 samples
  - DoS-UDP_Flood15.pcap_Flow.csv: 333 samples
  - DoS-UDP_Flood12.pcap_Flow.csv: 333 samples
  - DoS-UDP_Flood13.pcap_Flow.csv: 333 samples
  - DoS-UDP_Flood14.pcap_Flow.csv: 333 samples
  - DoS-UDP_Flood7.pcap_Flow.csv: 333 samples
  - DoS-UDP_Flood6.pcap_Flow.csv: 333 samples
  - DoS-UDP_Flood9.pcap_Flow.csv: 333 samples
  - DoS-UDP_Flood8.pcap_Flow.csv: 333 samples
  - DoS-UDP_Flood10.pcap_Flow.csv: 333 samples
  - DoS-SYN_Flood2.pcap_Flow.csv: 333 samples
  - DoS-SYN_Flood7.pcap_Flow.csv: 333 samples
  - DoS-SYN_Flood3.pcap_Flow.csv: 333 samples
  - DoS-SYN_Flood5.pcap_Flow.csv: 333 samples
  - DoS-SYN_Flood1.pcap_Flow.csv: 333 samples
  - DoS-SYN_Flood4.pcap_Flow.csv: 333 samples
  - DoS-SYN_Flood.pcap_Flow.csv: 333 samples
  - DoS-SYN_Flood6.pcap_Flow.csv: 333 samples
  - DoS-HTTP_Flood1.pcap_Flow.csv: 333 samples
  - DoS-HTTP_Flood.pcap_Flow.csv: 333 samples
  Total samples for DoS: 8325

Mirai: Found 29 CSV files
  - Mirai-greeth_flood27.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood8.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood22.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood26.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood2.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood14.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood10.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood13.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood7.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood15.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood18.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood19.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood16.pcap_Flow.csv: 344 samples
```

```
  - Mirai-greeth_flood24.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood25.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood23.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood28.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood12.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood21.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood9.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood1.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood11.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood20.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood17.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood3.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood4.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood6.pcap_Flow.csv: 344 samples
  - Mirai-greeth_flood5.pcap_Flow.csv: 344 samples
  Total samples for Mirai: 9976

Recon: Found 1 CSV files
  - VulnerabilityScan.pcap_Flow.csv: 10000 samples
  Total samples for Recon: 10000

Spoofing: Found 3 CSV files
  - DNS_Spoofing.pcap_Flow.csv: 3333 samples
  - MITM-ArpSpoofing.pcap_Flow.csv: 3333 samples
  - MITM-ArpSpoofing1.pcap_Flow.csv: 3333 samples
  Total samples for Spoofing: 9999

Web-Based: Found 3 CSV files
  - Uploading_Attack.pcap_Flow.csv: 1348 samples
  - SqlInjection.pcap_Flow.csv: 3333 samples
  - XSS.pcap_Flow.csv: 3333 samples
  Total samples for Web-Based: 8014

============================================================
Total dataset shape: (69876, 84)
Memory usage: 64.88 MB
```

In [341…

```python
# Display basic information about the dataset
print("Dataset Info:")
print("=" * 50)
print(f"Number of samples: {len(df)}")
print(f"Number of features: {len(df.columns)}")
print(f"\nColumn names:")
print(df.columns.tolist())
```

```
Dataset Info:
==================================================
Number of samples: 69876
Number of features: 84

Column names:
['Flow ID', 'Src IP', 'Src Port', 'Dst IP', 'Dst Port', 'Protocol', 'Times
tamp', 'Flow Duration', 'Total Fwd Packet', 'Total Bwd packets', 'Total Le
ngth of Fwd Packet', 'Total Length of Bwd Packet', 'Fwd Packet Length Ma
x', 'Fwd Packet Length Min', 'Fwd Packet Length Mean', 'Fwd Packet Length
Std', 'Bwd Packet Length Max', 'Bwd Packet Length Min', 'Bwd Packet Length
Mean', 'Bwd Packet Length Std', 'Flow Bytes/s', 'Flow Packets/s', 'Flow IA
T Mean', 'Flow IAT Std', 'Flow IAT Max', 'Flow IAT Min', 'Fwd IAT Total',
'Fwd IAT Mean', 'Fwd IAT Std', 'Fwd IAT Max', 'Fwd IAT Min', 'Bwd IAT Tota
l', 'Bwd IAT Mean', 'Bwd IAT Std', 'Bwd IAT Max', 'Bwd IAT Min', 'Fwd PSH
Flags', 'Bwd PSH Flags', 'Fwd URG Flags', 'Bwd URG Flags', 'Fwd Header Len
gth', 'Bwd Header Length', 'Fwd Packets/s', 'Bwd Packets/s', 'Packet Lengt
h Min', 'Packet Length Max', 'Packet Length Mean', 'Packet Length Std', 'P
acket Length Variance', 'FIN Flag Count', 'SYN Flag Count', 'RST Flag Coun
t', 'PSH Flag Count', 'ACK Flag Count', 'URG Flag Count', 'CWR Flag Coun
t', 'ECE Flag Count', 'Down/Up Ratio', 'Average Packet Size', 'Fwd Segment
Size Avg', 'Bwd Segment Size Avg', 'Fwd Bytes/Bulk Avg', 'Fwd Packet/Bulk
Avg', 'Fwd Bulk Rate Avg', 'Bwd Bytes/Bulk Avg', 'Bwd Packet/Bulk Avg', 'B
wd Bulk Rate Avg', 'Subflow Fwd Packets', 'Subflow Fwd Bytes', 'Subflow Bw
d Packets', 'Subflow Bwd Bytes', 'FWD Init Win Bytes', 'Bwd Init Win Byte
s', 'Fwd Act Data Pkts', 'Fwd Seg Size Min', 'Active Mean', 'Active Std',
'Active Max', 'Active Min', 'Idle Mean', 'Idle Std', 'Idle Max', 'Idle Mi
n', 'Label']
```

In [342…

```python
# Display first few rows
df.head()
```

Out[342…

	Flow ID	Src IP	Src Port	Dst IP	Dst Port	Protocol	Timesta
0	192.168.137.175-52.30.149.214-40788-443-6	192.168.137.175	40788	52.30.149.214	443	6	08/10/2(02:47
1	192.168.137.172-151.101.1.16-46966-443-6	192.168.137.172	46966	151.101.1.16	443	6	08/10/2(02:47
2	192.168.137.90-239.255.255.250-37020-37000-17	192.168.137.90	37020	239.255.255.250	37000	17	08/10/2(02:47
3	192.168.137.58-192.168.137.253-56902-1243-6	192.168.137.58	56902	192.168.137.253	1243	6	08/10/2(02:49
4	192.168.137.58-192.168.137.148-43050-1400-6	192.168.137.58	43050	192.168.137.148	1400	6	08/10/2(02:49

5 rows × 84 columns

In [343…

```python
# Data types and missing values
print("Data Types:")
```

```
print(df.dtypes)
print("\nMissing Values:")
missing = df.isnull().sum()
missing_pct = (missing / len(df)) * 100
missing_df = pd.DataFrame({'Missing Count': missing, 'Percentage': missin
print(missing_df[missing_df['Missing Count'] > 0])
```

```
Data Types:
Flow ID        object
Src IP         object
Src Port        int64
Dst IP         object
Dst Port        int64
                ...
Idle Mean     float64
Idle Std      float64
Idle Max      float64
Idle Min      float64
Label          object
Length: 84, dtype: object

Missing Values:
              Missing Count  Percentage
Flow Bytes/s             74    0.105902
```

In [344…

```
# Statistical summary
df.describe()
```

Out[344…

	Src Port	Dst Port	Protocol	Flow Duration	Total Fwd Packet	
count	69876.000000	69876.000000	69876.000000	6.987600e+04	69876.000000	698
mean	33921.624850	14708.951271	12.219231	2.400336e+07	337.544765	
std	21408.960217	20158.351458	5.641490	4.069503e+07	10010.843623	19
min	0.000000	0.000000	0.000000	0.000000e+00	1.000000	
25%	12958.250000	53.000000	6.000000	5.846075e+04	1.000000	
50%	40307.500000	1443.000000	17.000000	2.751805e+05	2.000000	
75%	51549.750000	32100.000000	17.000000	3.199588e+07	5.000000	
max	65531.000000	65523.000000	17.000000	1.200000e+08	969425.000000	3837

8 rows × 79 columns

3. Dataset Characterization

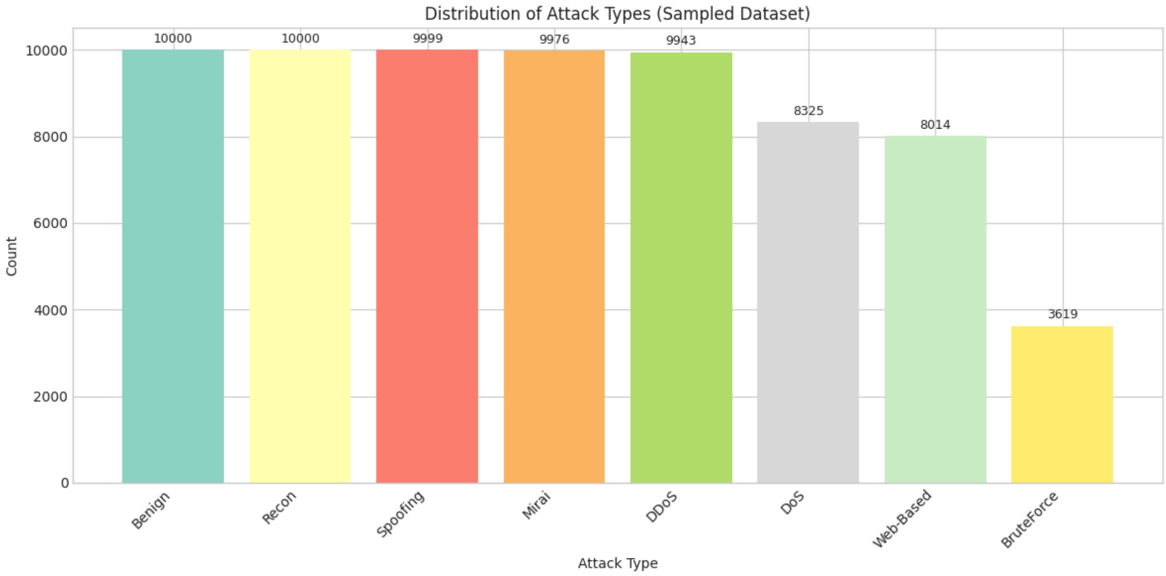
In [345…

```
# Label distribution
label_col = 'Label'
print(f"Label column: {label_col}")
print(f"\nLabel distribution:")
label_counts = df[label_col].value_counts()
print(label_counts)
```

```
Label column: Label

Label distribution:
Label
Benign        10000
Recon         10000
Spoofing       9999
Mirai          9976
DDoS           9943
DoS            8325
Web-Based      8014
BruteForce     3619
Name: count, dtype: int64
```

In [346…

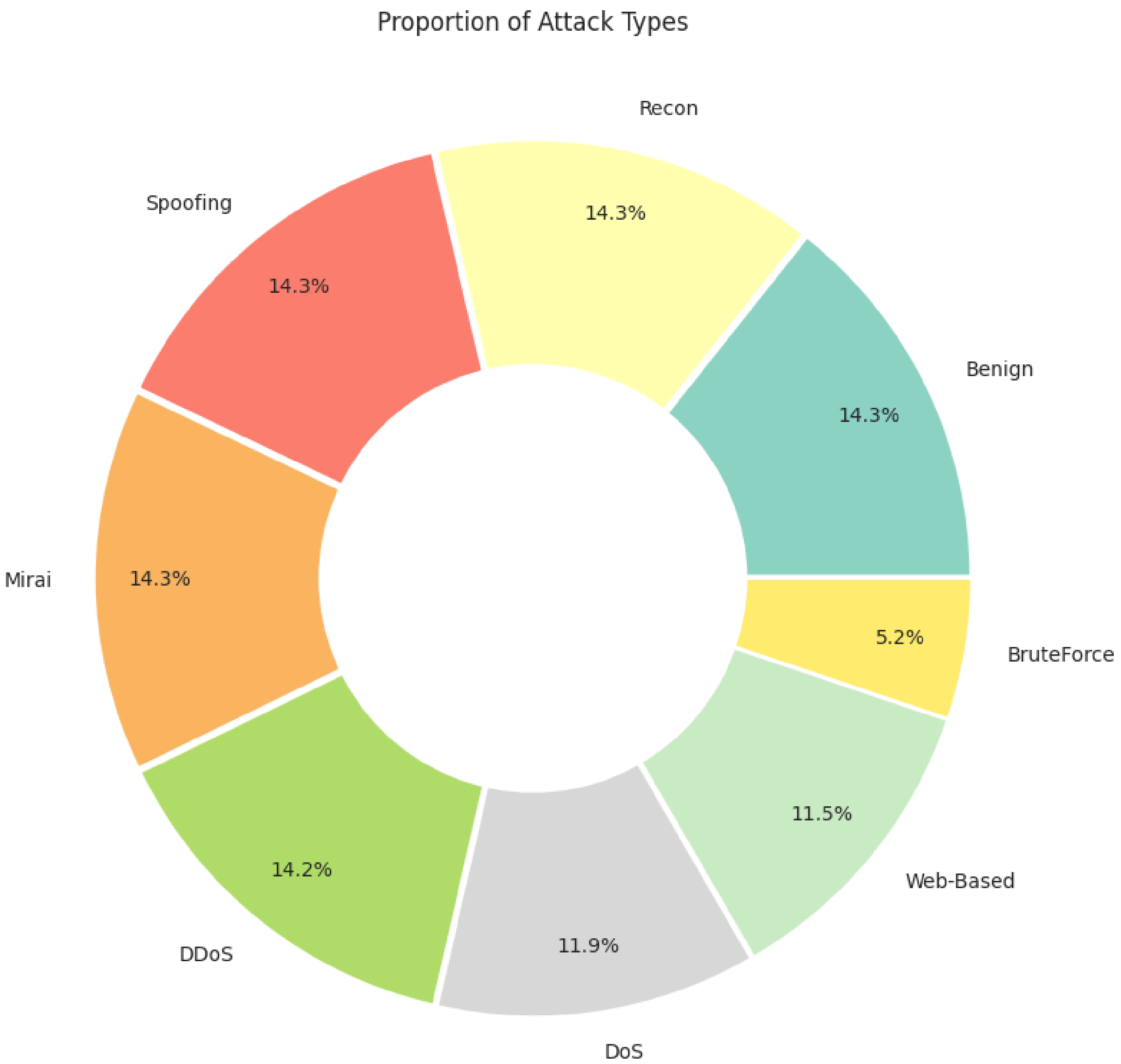
```
# Visualize label distribution
fig, ax = plt.subplots(figsize=(12, 6))
colors = plt.cm.Set3(np.linspace(0, 1, len(label_counts)))
bars = ax.bar(label_counts.index, label_counts.values, color=colors)
ax.set_xlabel('Attack Type')
ax.set_ylabel('Count')
ax.set_title('Distribution of Attack Types (Sampled Dataset)')
plt.xticks(rotation=45, ha='right')
for bar, count in zip(bars, label_counts.values):
    ax.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 100, f'{c
plt.tight_layout()
plt.show()
```



In [347…

```
# Pie chart for label distribution
fig, ax = plt.subplots(figsize=(10, 8))
colors = plt.cm.Set3(np.linspace(0, 1, len(label_counts)))
wedges, texts, autotexts = ax.pie(
    label_counts.values,
    labels=label_counts.index,
    autopct='%1.1f%%',
    colors=colors,
    pctdistance=0.85,
    explode=[0.02] * len(label_counts)
)
centre_circle = plt.Circle((0, 0), 0.50, fc='white')
ax.add_patch(centre_circle)
ax.set_title('Proportion of Attack Types')
```

```
plt.tight_layout()
plt.show()
```



In [348…

```
# Create binary label for anomaly detection (Benign vs Attack)
df['is_attack'] = (df[label_col] != 'Benign').astype(int)

print("Binary Classification Distribution:")
print(df['is_attack'].value_counts())
print(f"\nAttack ratio: {df['is_attack'].mean()*100:.2f}%")
```

```
Binary Classification Distribution:
is_attack
1    59876
0    10000
Name: count, dtype: int64

Attack ratio: 85.69%
```

4. Data Preprocessing

In [349…

```
# Keep a copy of labels
y_multiclass = df[label_col].copy()
y_binary = df['is_attack'].copy()
```

```python
# Drop label columns from features
df_features = df.drop(columns=[label_col, 'is_attack'])

print(f"Features shape: {df_features.shape}")
```

```
Features shape: (69876, 83)
```

In [350…

```python
# Handle non-numeric columns
non_numeric_cols = df_features.select_dtypes(include=['object']).columns.
print(f"Non-numeric columns: {non_numeric_cols}")

# Drop IP addresses and similar identifier columns
cols_to_drop = [col for col in non_numeric_cols if any(x in col.lower() f
df_features = df_features.drop(columns=cols_to_drop, errors='ignore')

# Label encode remaining categorical columns
remaining_object_cols = df_features.select_dtypes(include=['object']).col
le = LabelEncoder()
for col in remaining_object_cols:
    df_features[col] = le.fit_transform(df_features[col].astype(str))

print(f"Features shape after encoding: {df_features.shape}")
```

```
Non-numeric columns: ['Flow ID', 'Src IP', 'Dst IP', 'Timestamp']
Features shape after encoding: (69876, 79)
```

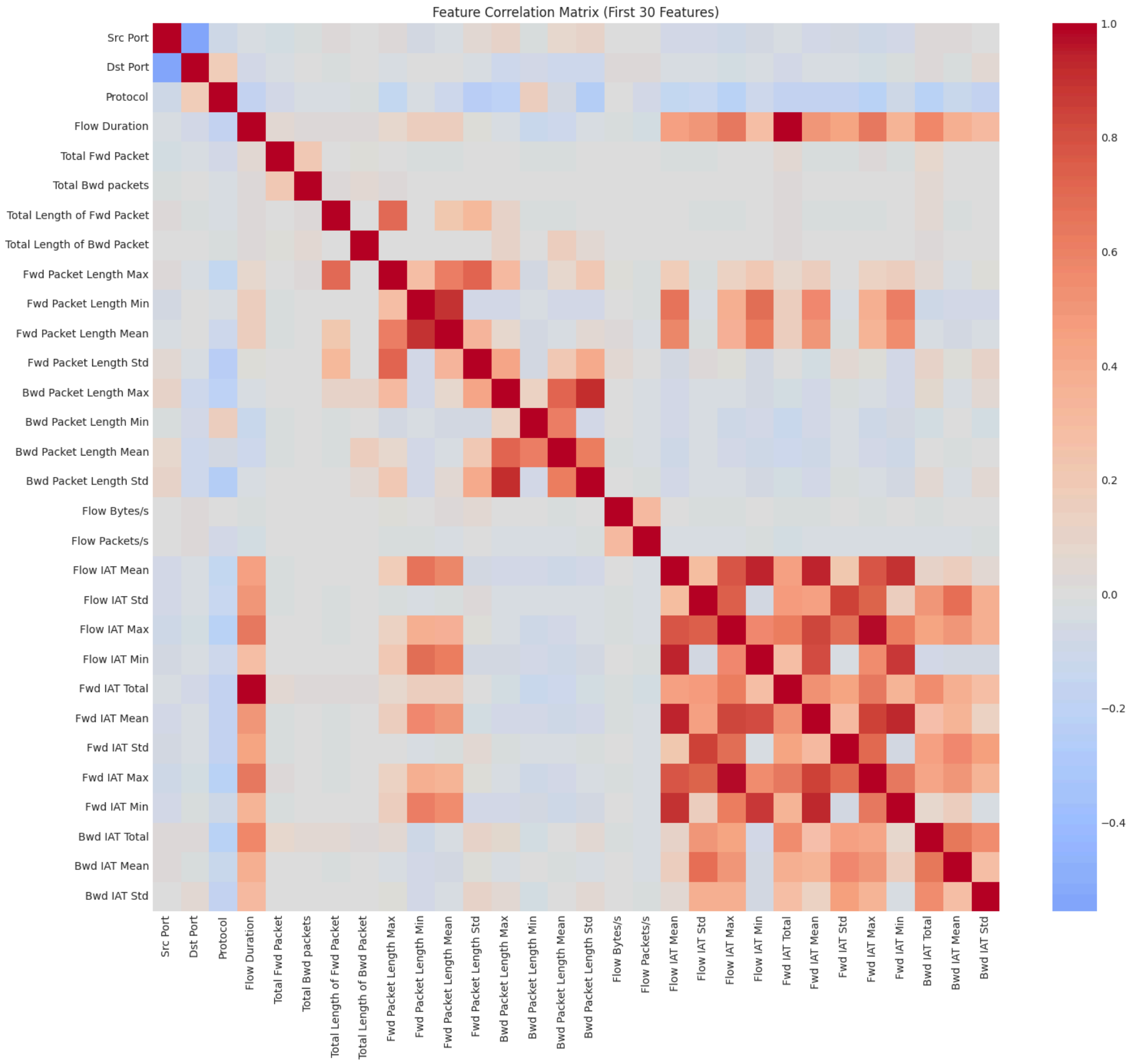
In [351…

```python
# Handle infinite values and fill missing values
df_features = df_features.replace([np.inf, -np.inf], np.nan)

# Fill missing values with median
for col in df_features.columns:
    if df_features[col].isnull().any():
        median_val = df_features[col].median()
        df_features[col] = df_features[col].fillna(median_val if pd.notna

# Remove constant columns (variance = 0)
constant_cols = df_features.columns[df_features.nunique() <= 1].tolist()
df_features = df_features.drop(columns=constant_cols)
print(f"Removed {len(constant_cols)} constant columns")
print(f"Final features shape: {df_features.shape}")
```

```
Removed 7 constant columns
Final features shape: (69876, 72)
```

In [352…

```python
# Feature correlation analysis (sample for visualization)
plt.figure(figsize=(16, 14))
sample_cols = df_features.columns[:min(30, len(df_features.columns))]
corr_matrix = df_features[sample_cols].corr()
sns.heatmap(corr_matrix, cmap='coolwarm', center=0, annot=False)
plt.title('Feature Correlation Matrix (First 30 Features)')
plt.tight_layout()
plt.show()
```



In [353…

```
# Encode multiclass labels
le_multiclass = LabelEncoder()
y_multiclass_encoded = le_multiclass.fit_transform(y_multiclass)
class_names = le_multiclass.classes_
print(f"Classes: {class_names}")
print(f"Number of classes: {len(class_names)}")
```

```
Classes: ['Benign' 'BruteForce' 'DDoS' 'DoS' 'Mirai' 'Recon' 'Spoofing' 'W
eb-Based']
Number of classes: 8
```

In [354…

```
# Split data for training and testing
X = df_features.values
y = y_binary.values  # Binary classification
y_multi = y_multiclass_encoded  # Multiclass classification

# Train-test split (binary)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=RANDOM_STATE, stratify=y
)

# Train-test split (multiclass)
X_train_multi, X_test_multi, y_train_multi, y_test_multi = train_test_spl
    X, y_multi, test_size=0.2, random_state=RANDOM_STATE, stratify=y_mult
)
```

```
print(f"Training set: {X_train.shape}")
print(f"Test set: {X_test.shape}")
```

```
Training set: (55900, 72)
Test set: (13976, 72)
```

In [355…

```
# Scale features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

X_train_multi_scaled = scaler.fit_transform(X_train_multi)
X_test_multi_scaled = scaler.transform(X_test_multi)

print("Features scaled successfully!")
```

```
Features scaled successfully!
```

5. Unsupervised Learning - Anomaly Detection

We benchmark 3 complementary unsupervised algorithms:

1. **Isolation Forest** - Tree-based anomaly detection
2. **Local Outlier Factor (LOF)** - Density-based anomaly detection
3. **One-Class SVM** - Support vector-based anomaly detection

In [356…

```
def evaluate_anomaly_detector(y_true, y_pred, model_name):
    """Evaluate anomaly detection model and return metrics."""
    # Convert predictions: -1 (anomaly) -> 1 (attack), 1 (normal) -> 0
    y_pred_binary = np.where(y_pred == -1, 1, 0)

    cm = confusion_matrix(y_true, y_pred_binary)
    precision = precision_score(y_true, y_pred_binary, zero_division=0)
    recall = recall_score(y_true, y_pred_binary, zero_division=0)
    f1 = f1_score(y_true, y_pred_binary, zero_division=0)
    balanced_acc = balanced_accuracy_score(y_true, y_pred_binary)
    mcc = matthews_corrcoef(y_true, y_pred_binary)

    print(f"\n{'='*50}")
    print(f"Model: {model_name}")
    print(f"{'='*50}")
    print(f"Confusion Matrix:\n{cm}")
    print(f"Precision: {precision:.4f}")
    print(f"Recall: {recall:.4f}")
    print(f"F1-Score: {f1:.4f}")
    print(f"Balanced Accuracy: {balanced_acc:.4f}")
    print(f"Matthews Correlation Coefficient: {mcc:.4f}")

    # Plot confusion matrix
    fig, ax = plt.subplots(figsize=(6, 5))
    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['B
    disp.plot(ax=ax, cmap='Blues')
    plt.title(f'Confusion Matrix - {model_name}')
    plt.tight_layout()
    plt.show()

    return {
        'Model': model_name,
```

```
        'Precision': precision,
        'Recall': recall,
        'F1-Score': f1,
        'Balanced Accuracy': balanced_acc,
        'MCC': mcc
    }
```

In [357…

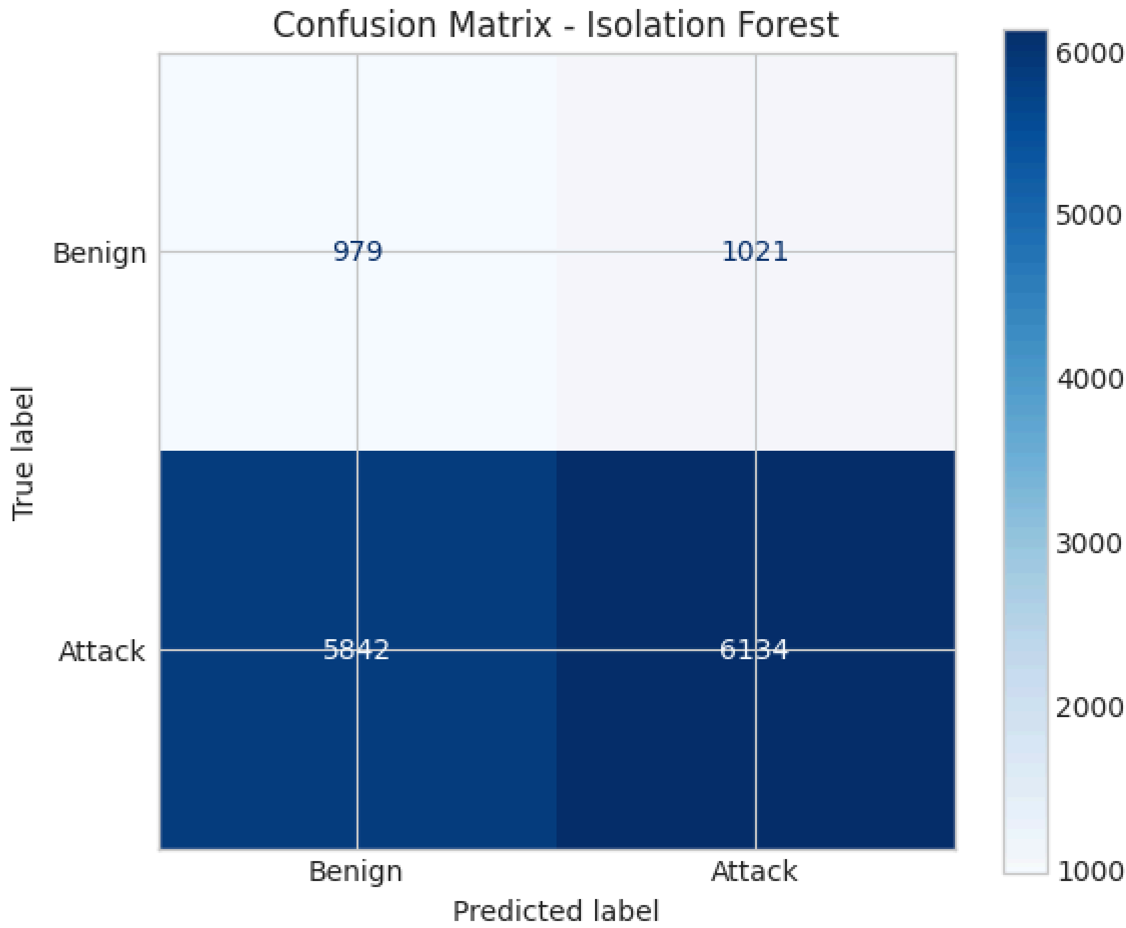
```
# Calculate contamination rate (proportion of attacks)
contamination_rate = y_train.mean()
print(f"Contamination rate (attack ratio): {contamination_rate:.4f}")
```

```
Contamination rate (attack ratio): 0.8569
```

In [358…

```
# 1. Isolation Forest - IMPROVED (trained on benign samples only)
print("Training Isolation Forest on benign samples only...")

# CRITICAL FIX: Train only on benign samples
X_train_benign_ad = X_train_scaled[y_train == 0]
print(f"Training on {len(X_train_benign_ad)} benign samples")

iso_forest = IsolationForest(
    n_estimators=200,  # More trees for stability
    max_samples='auto',
    contamination=0.5,  # High recall threshold
    random_state=RANDOM_STATE,
    n_jobs=-1,
    bootstrap=True  # Better variance estimation
)
iso_forest.fit(X_train_benign_ad)

# Predict on test set
y_pred_iso = iso_forest.predict(X_test_scaled)
iso_results = evaluate_anomaly_detector(y_test, y_pred_iso, "Isolation Fo
```

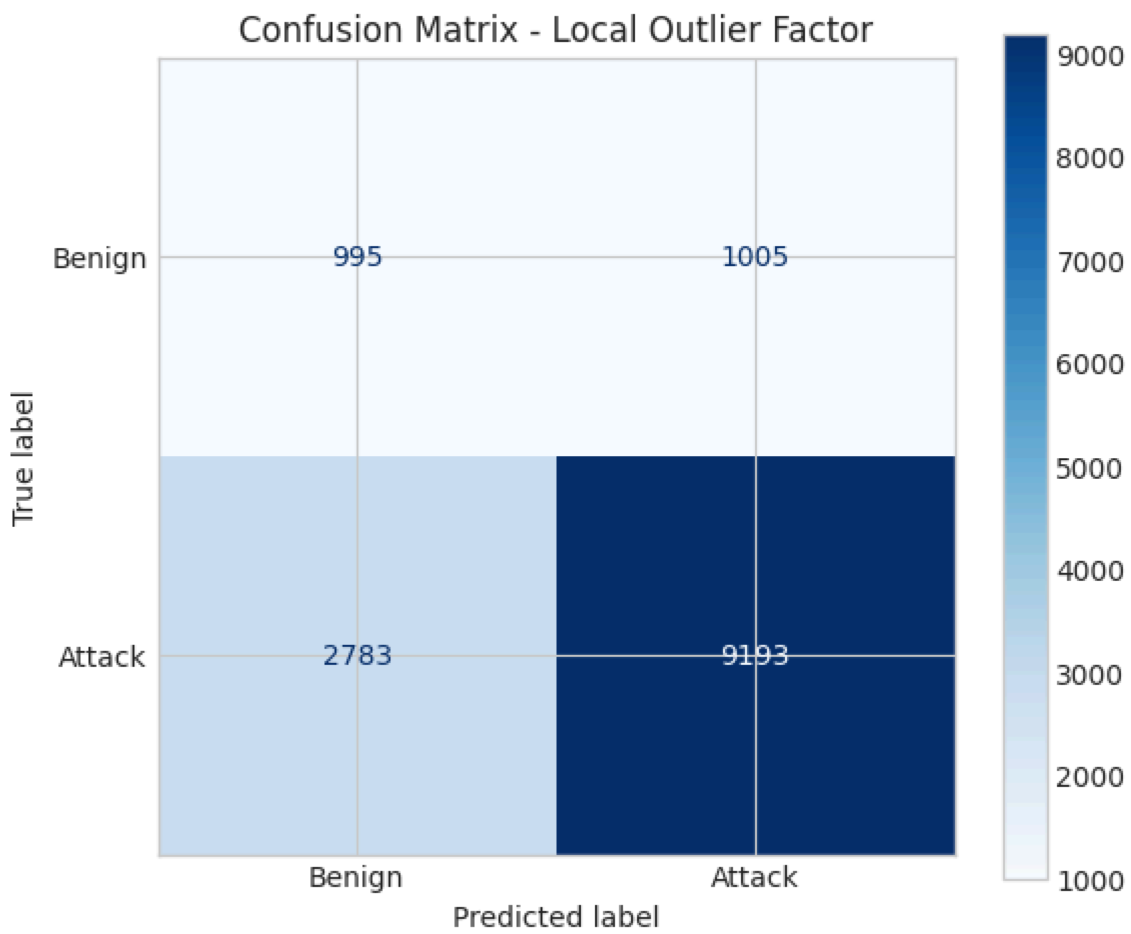
```
Training Isolation Forest on benign samples only...
Training on 8000 benign samples

==================================================
Model: Isolation Forest
==================================================
Confusion Matrix:
[[ 979 1021]
 [5842 6134]]
Precision: 0.8573
Recall: 0.5122
F1-Score: 0.6413
Balanced Accuracy: 0.5008
Matthews Correlation Coefficient: 0.0012
```



In [359…

```
# 2. Local Outlier Factor - IMPROVED (trained on benign samples only)
print("Training Local Outlier Factor on benign samples only...")

lof = LocalOutlierFactor(
    n_neighbors=30,  # Increased for better local structure
    contamination=0.5,
    novelty=True,
    n_jobs=-1,
    metric='euclidean'
)
lof.fit(X_train_benign_ad)  # Use benign samples from IF cell
y_pred_lof = lof.predict(X_test_scaled)
lof_results = evaluate_anomaly_detector(y_test, y_pred_lof, "Local Outlie
```

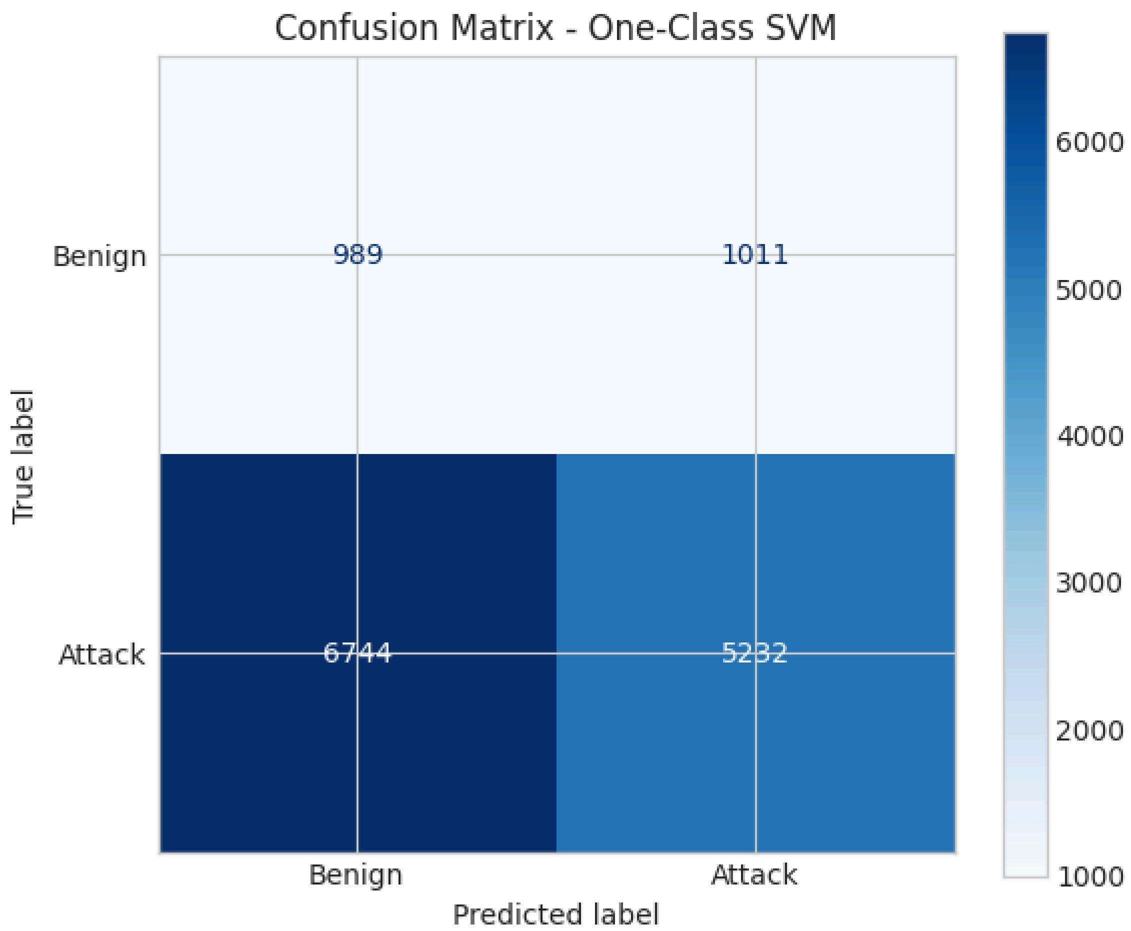
```
Training Local Outlier Factor on benign samples only...

==================================================
Model: Local Outlier Factor
==================================================
Confusion Matrix:
[[ 995 1005]
 [2783 9193]]
Precision: 0.9015
Recall: 0.7676
F1-Score: 0.8292
Balanced Accuracy: 0.6326
Matthews Correlation Coefficient: 0.2090
```



In [360…

```
# 3. One-Class SVM - IMPROVED (trained on benign samples only)
print("Training One-Class SVM on benign samples only...")

# Use benign samples with subsampling for efficiency
OCSVM_MAX_SAMPLES = 10000
if len(X_train_benign_ad) > OCSVM_MAX_SAMPLES:
    ocsvm_idx = np.random.choice(len(X_train_benign_ad), OCSVM_MAX_SAMPLE
    X_train_ocsvm = X_train_benign_ad[ocsvm_idx]
else:
    X_train_ocsvm = X_train_benign_ad

ocsvm = OneClassSVM(
    kernel='rbf',
    gamma='scale',
    nu=0.5  # Expect ~50% of benign as outliers
)
ocsvm.fit(X_train_ocsvm)
y_pred_ocsvm = ocsvm.predict(X_test_scaled)
ocsvm_results = evaluate_anomaly_detector(y_test, y_pred_ocsvm, "One-Clas
```

```
Training One-Class SVM on benign samples only...

==================================================
Model: One-Class SVM
==================================================
Confusion Matrix:
[[ 989 1011]
 [6744 5232]]
Precision: 0.8381
Recall: 0.4369
F1-Score: 0.5743
Balanced Accuracy: 0.4657
Matthews Correlation Coefficient: -0.0483
```



Algorithm 4: Autoencoder (Deep Learning)

We implement a deep Autoencoder trained only on benign traffic. Anomalies are detected based on high reconstruction error.

In [361…

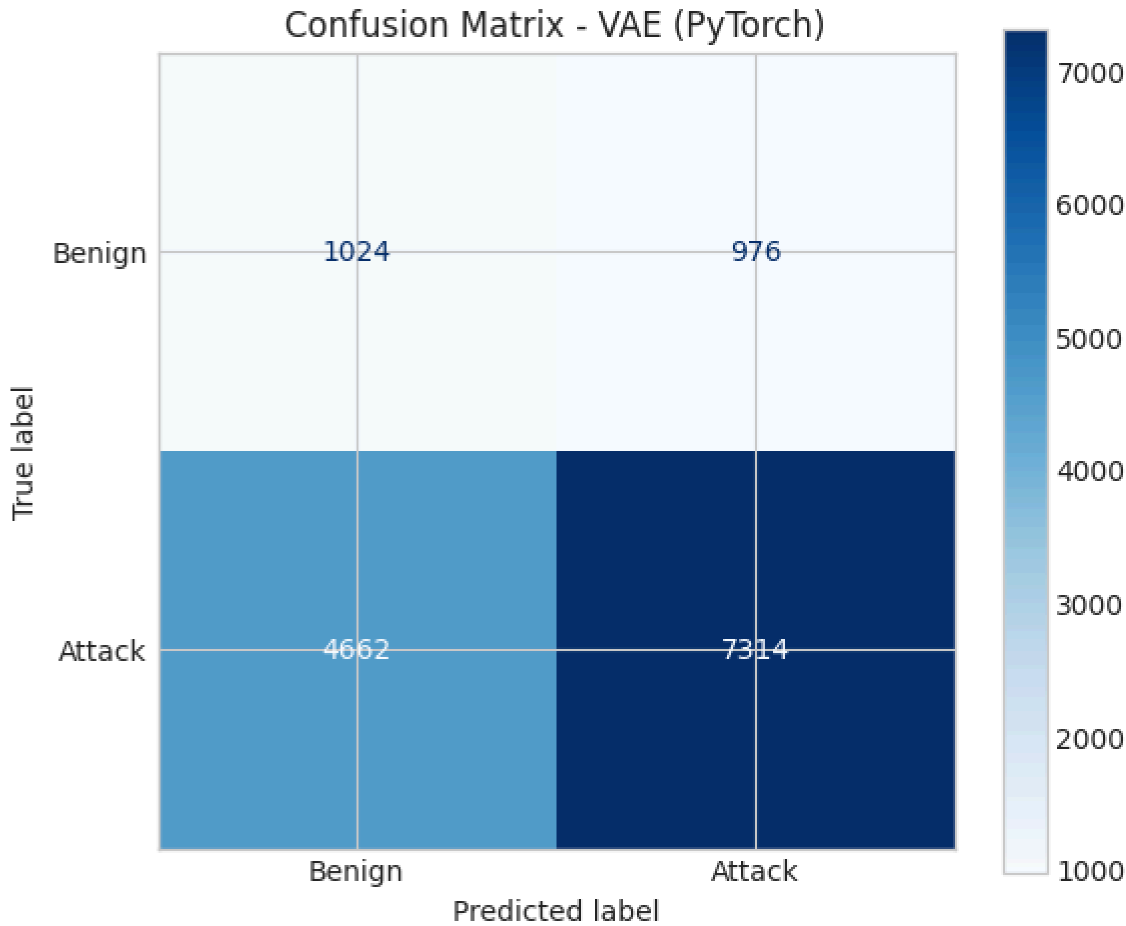
```python
# 4. Improved Variational Autoencoder (VAE) - Deeper Architecture
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset

class ImprovedVAE(nn.Module):
    def __init__(self, input_dim, latent_dim=32):
        super(ImprovedVAE, self).__init__()
        # Deeper Encoder with BatchNorm
```

```
        self.encoder = nn.Sequential(
            nn.Linear(input_dim, 256),
            nn.BatchNorm1d(256),
            nn.LeakyReLU(0.2),
            nn.Dropout(0.2),
            nn.Linear(256, 128),
            nn.BatchNorm1d(128),
            nn.LeakyReLU(0.2),
            nn.Linear(128, 64),
            nn.LeakyReLU(0.2)
        )
        self.fc_mu = nn.Linear(64, latent_dim)
        self.fc_logvar = nn.Linear(64, latent_dim)

        # Symmetric Decoder
        self.decoder = nn.Sequential(
            nn.Linear(latent_dim, 64),
            nn.LeakyReLU(0.2),
            nn.Linear(64, 128),
            nn.BatchNorm1d(128),
            nn.LeakyReLU(0.2),
            nn.Linear(128, 256),
            nn.BatchNorm1d(256),
            nn.LeakyReLU(0.2),
            nn.Linear(256, input_dim)
        )

    def encode(self, x):
        h = self.encoder(x)
        return self.fc_mu(h), self.fc_logvar(h)

    def reparameterize(self, mu, logvar):
        std = torch.exp(0.5 * logvar)
        eps = torch.randn_like(std)
        return mu + eps * std

    def decode(self, z):
        return self.decoder(z)

    def forward(self, x):
        mu, logvar = self.encode(x)
        z = self.reparameterize(mu, logvar)
        return self.decode(z), mu, logvar

def vae_loss_function(recon_x, x, mu, logvar, beta=0.5):
    MSE = F.mse_loss(recon_x, x, reduction='sum')
    KLD = -0.5 * torch.sum(1 + logvar - mu.pow(2) - logvar.exp())
    return MSE + beta * KLD  # Beta-VAE for better latent space

print("Training Improved VAE (PyTorch)...")

# Prepare benign training data
X_train_benign = X_train_scaled[y_train == 0]
X_train_benign_tensor = torch.FloatTensor(X_train_benign)
X_test_tensor = torch.FloatTensor(X_test_scaled)

# Device setup
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(f"Using device: {device}")
```

```
input_dim = X_train_scaled.shape[1]
vae = ImprovedVAE(input_dim, latent_dim=32).to(device)
optimizer = optim.AdamW(vae.parameters(), lr=0.001, weight_decay=1e-5)
scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer, mode='min', p

train_loader = DataLoader(
    TensorDataset(X_train_benign_tensor, X_train_benign_tensor),
    batch_size=128,
    shuffle=True
)

# Train with more epochs and early stopping
vae.train()
best_loss = float('inf')
patience_counter = 0

for epoch in range(300):
    train_loss = 0
    for batch_x, _ in train_loader:
        batch_x = batch_x.to(device)
        optimizer.zero_grad()
        recon_batch, mu, logvar = vae(batch_x)
        loss = vae_loss_function(recon_batch, batch_x, mu, logvar)
        loss.backward()
        torch.nn.utils.clip_grad_norm_(vae.parameters(), 1.0)
        train_loss += loss.item()
        optimizer.step()

    avg_loss = train_loss / len(train_loader)
    scheduler.step(avg_loss)

    # Early stopping
    if avg_loss < best_loss:
        best_loss = avg_loss
        patience_counter = 0
    else:
        patience_counter += 1
        if patience_counter >= 10:
            print(f"Early stopping at epoch {epoch+1}")
            break

    if (epoch + 1) % 10 == 0:
        print(f"Epoch {epoch+1}/50, Loss: {avg_loss:.4f}")

# Evaluate
vae.eval()
with torch.no_grad():
    X_test_device = X_test_tensor.to(device)
    reconstructions, _, _ = vae(X_test_device)
    reconstructions = reconstructions.cpu().numpy()
    mse = np.mean(np.power(X_test_scaled - reconstructions, 2), axis=1)

# Optimized threshold using validation set
with torch.no_grad():
    X_benign_device = X_train_benign_tensor.to(device)
    train_recon, _, _ = vae(X_benign_device)
    train_recon = train_recon.cpu().numpy()
    train_mse = np.mean(np.power(X_train_benign - train_recon, 2), axis=1

# Use 50th percentile (median) for better recall
```

```python
threshold = np.percentile(train_mse, 50)
print(f"VAE Threshold (50th percentile (median)): {threshold:.6f}")

y_pred_vae = (mse > threshold).astype(int)
y_pred_vae_formatted = np.where(y_pred_vae == 1, -1, 1)

vae_results = evaluate_anomaly_detector(y_test, y_pred_vae_formatted, "VA
```

```
Training Improved VAE (PyTorch)...
Using device: cuda
Epoch 10/50, Loss: 2168.6685
Epoch 20/50, Loss: 1650.8636
Epoch 30/50, Loss: 1409.2110
Epoch 40/50, Loss: 1278.3571
Epoch 50/50, Loss: 1195.5107
Epoch 60/50, Loss: 1147.8437
Epoch 70/50, Loss: 1115.5988
Epoch 80/50, Loss: 960.6780
Epoch 90/50, Loss: 934.9484
Epoch 100/50, Loss: 921.4447
Epoch 110/50, Loss: 894.0678
Epoch 120/50, Loss: 875.2485
Epoch 130/50, Loss: 883.7456
Early stopping at epoch 139
VAE Threshold (50th percentile (median)): 0.018372

==================================================
Model: VAE (PyTorch)
==================================================
Confusion Matrix:
[[1024  976]
 [4662 7314]]
Precision: 0.8823
Recall: 0.6107
F1-Score: 0.7218
Balanced Accuracy: 0.5614
Matthews Correlation Coefficient: 0.0875
```



In [382…

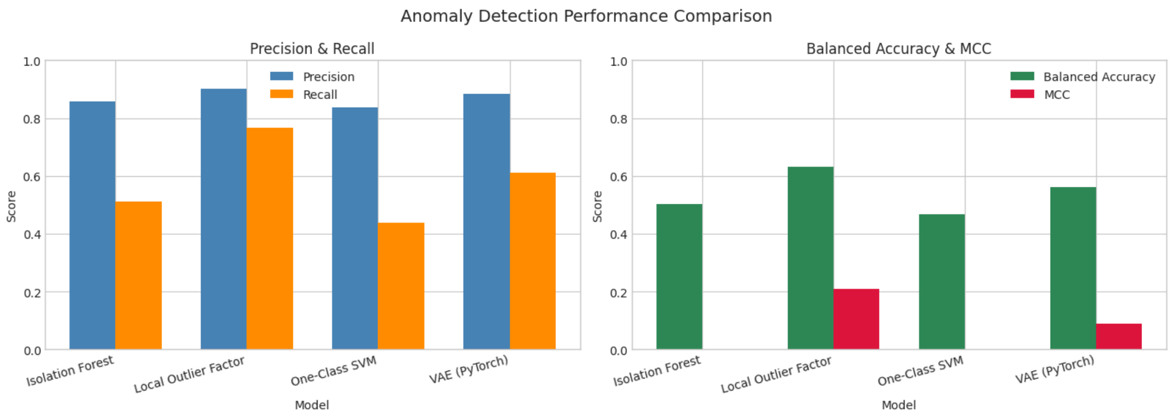
```
# Summary of Anomaly Detection Results
anomaly_results_df = pd.DataFrame([iso_results, lof_results, ocsvm_result
print("\n" + "="*70)
print("ANOMALY DETECTION BENCHMARK SUMMARY")
print("="*70)
print(anomaly_results_df.to_string(index=False))
```

```
======================================================================
ANOMALY DETECTION BENCHMARK SUMMARY
======================================================================
               Model  Precision   Recall  F1-Score  Balanced Accuracy
MCC
    Isolation Forest   0.857303 0.512191  0.641263           0.500846  0.0
01185
Local Outlier Factor   0.901451 0.767619  0.829169           0.632559  0.2
09037
       One-Class SVM   0.838059 0.436874  0.574345           0.465687 -0.0
48338
       VAE (PyTorch)   0.882268 0.610721  0.721800           0.561361  0.0
87480
```

In [383…

```
# Visualize anomaly detection results
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

models = anomaly_results_df['Model'].tolist()
x = np.arange(len(models))
width = 0.35

# Precision & Recall
axes[0].bar(x - width/2, anomaly_results_df['Precision'], width, label='P
axes[0].bar(x + width/2, anomaly_results_df['Recall'], width, label='Reca
```

```
axes[0].set_xlabel('Model')
axes[0].set_ylabel('Score')
axes[0].set_title('Precision & Recall')
axes[0].set_xticks(x)
axes[0].set_xticklabels(models, rotation=15, ha='right')
axes[0].legend()
axes[0].set_ylim(0, 1)

# Balanced Accuracy & MCC
axes[1].bar(x - width/2, anomaly_results_df['Balanced Accuracy'], width,
axes[1].bar(x + width/2, anomaly_results_df['MCC'], width, label='MCC', c
axes[1].set_xlabel('Model')
axes[1].set_ylabel('Score')
axes[1].set_title('Balanced Accuracy & MCC')
axes[1].set_xticks(x)
axes[1].set_xticklabels(models, rotation=15, ha='right')
axes[1].legend()
axes[1].set_ylim(0, 1)

plt.suptitle('Anomaly Detection Performance Comparison', fontsize=14)
plt.tight_layout()
plt.show()
```



6. Supervised Learning - Classification

We benchmark 3 complementary classification algorithms:

1. **Random Forest** - Ensemble tree-based classifier
2. **XGBoost** - Gradient boosting classifier
3. **LightGBM** - Light gradient boosting classifier

In [364…

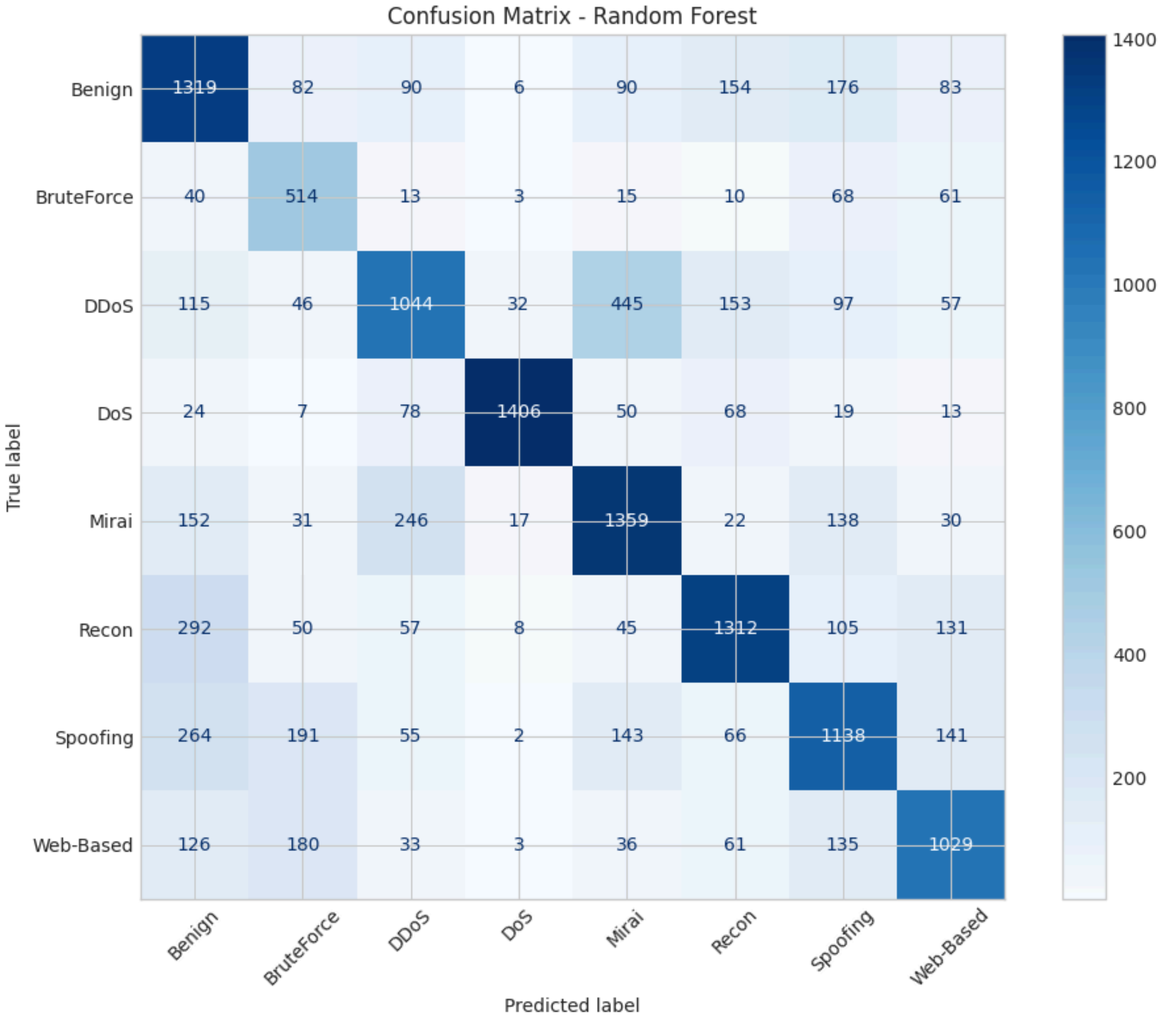
```
def evaluate_classifier(model, X_train, X_test, y_train, y_test, model_na
    """Train and evaluate a classifier with comprehensive metrics."""
    print(f"Training {model_name}...")
    model.fit(X_train, y_train)

    # Predictions
    y_pred = model.predict(X_test)

    # Probabilities for AUPRC
    if hasattr(model, 'predict_proba'):
        y_prob = model.predict_proba(X_test)
        try:
            from sklearn.preprocessing import label_binarize
```

```
            y_test_bin = label_binarize(y_test, classes=range(len(class_n
            auprc = average_precision_score(y_test_bin, y_prob, average='
        except:
            auprc = 0.0
    else:
        auprc = 0.0

    # Metrics
    cm = confusion_matrix(y_test, y_pred)
    precision = precision_score(y_test, y_pred, average='weighted', zero_
    recall = recall_score(y_test, y_pred, average='weighted', zero_divisi
    balanced_acc = balanced_accuracy_score(y_test, y_pred)
    mcc = matthews_corrcoef(y_test, y_pred)

    print(f"\n{'='*50}")
    print(f"Model: {model_name}")
    print(f"{'='*50}")
    print(f"Precision (weighted): {precision:.4f}")
    print(f"Recall (weighted): {recall:.4f}")
    print(f"AUPRC (weighted): {auprc:.4f}")
    print(f"Balanced Accuracy: {balanced_acc:.4f}")
    print(f"Matthews Correlation Coefficient: {mcc:.4f}")

    # Plot confusion matrix
    fig, ax = plt.subplots(figsize=(10, 8))
    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=cla
    disp.plot(ax=ax, cmap='Blues', xticks_rotation=45)
    plt.title(f'Confusion Matrix - {model_name}')
    plt.tight_layout()
    plt.show()

    return {
        'Model': model_name,
        'Precision': precision,
        'Recall': recall,
        'AUPRC': auprc,
        'Balanced Accuracy': balanced_acc,
        'MCC': mcc
    }, model
```

In [365…

```
# 1. Random Forest Classifier - IMPROVED
rf = RandomForestClassifier(
    n_estimators=200,  # More trees
    max_depth=25,  # Deeper trees
    min_samples_split=5,
    min_samples_leaf=2,
    max_features='sqrt',
    random_state=RANDOM_STATE,
    n_jobs=-1,
    class_weight='balanced',
    bootstrap=True,
    oob_score=True  # Out-of-bag score for validation
)
rf_results, rf_model = evaluate_classifier(
    rf, X_train_multi_scaled, X_test_multi_scaled, y_train_multi, y_test_
    "Random Forest", class_names
)
print(f"OOB Score: {rf_model.oob_score_:.4f}")
```

```
Training Random Forest...

==================================================
Model: Random Forest
==================================================
Precision (weighted): 0.6642
Recall (weighted): 0.6526
AUPRC (weighted): 0.7312
Balanced Accuracy: 0.6609
Matthews Correlation Coefficient: 0.6016
```



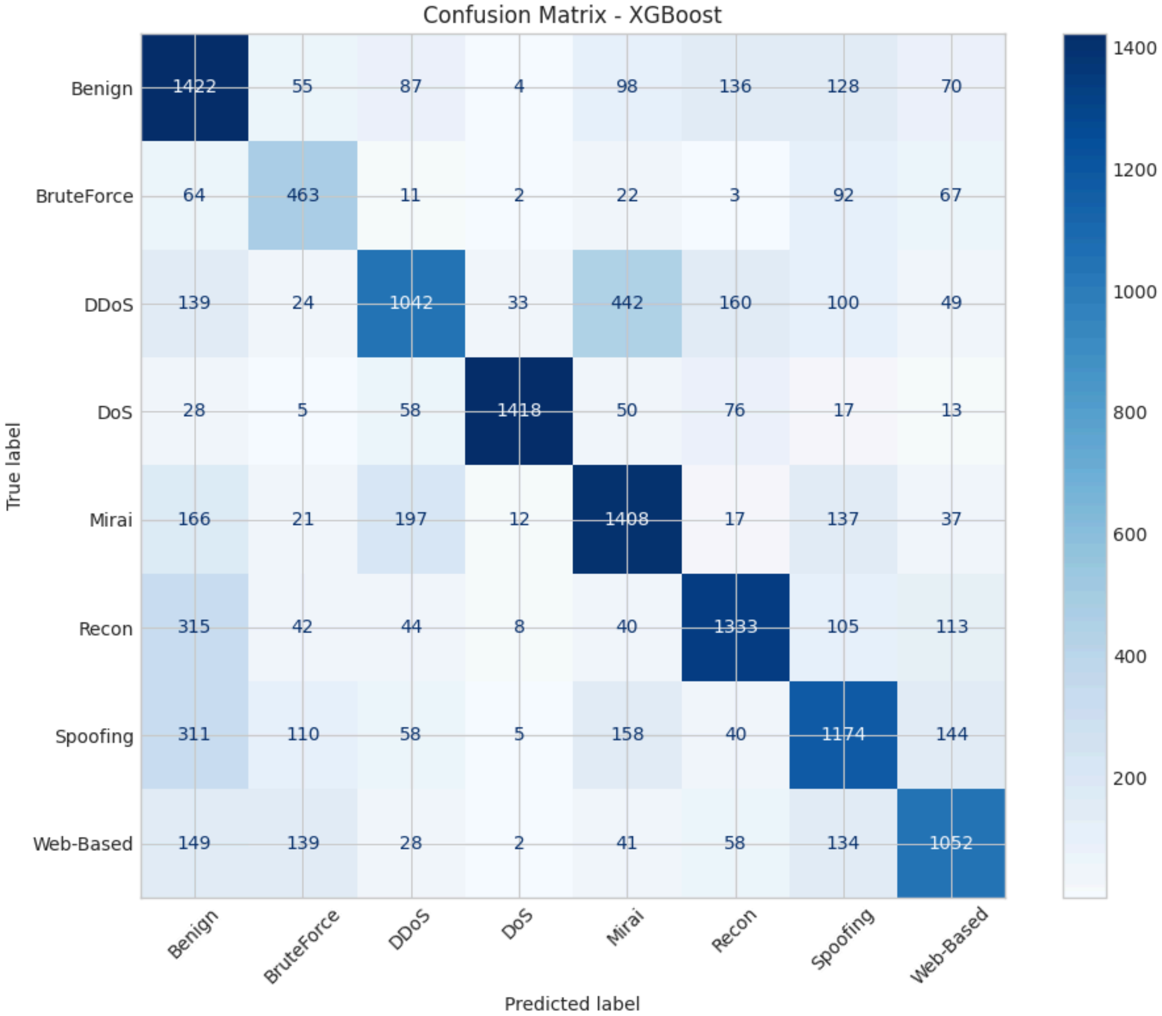

```
OOB Score: 0.6469
```

In [366…

```
# 2. XGBoost Classifier - IMPROVED
# Calculate scale_pos_weight for imbalanced classes
class_counts = np.bincount(y_train_multi)
total_samples = len(y_train_multi)

xgb = XGBClassifier(
    n_estimators=300,  # More trees
    max_depth=8,
    learning_rate=0.05,  # Lower LR with more trees
    subsample=0.8,  # Row subsampling
    colsample_bytree=0.8,  # Feature subsampling
    min_child_weight=5,
    reg_alpha=0.1,  # L1 regularization
    reg_lambda=1.0,  # L2 regularization
    gamma=0.1,  # Minimum loss reduction
    random_state=RANDOM_STATE,
    n_jobs=-1,
```

```
    eval_metric='mlogloss',
    verbosity=0,
    tree_method='hist'  # Faster training
)
xgb_results, xgb_model = evaluate_classifier(
    xgb, X_train_multi_scaled, X_test_multi_scaled, y_train_multi, y_test
    "XGBoost", class_names
)
```

```
Training XGBoost...

==================================================
Model: XGBoost
==================================================
Precision (weighted): 0.6782
Recall (weighted): 0.6663
AUPRC (weighted): 0.7544
Balanced Accuracy: 0.6677
Matthews Correlation Coefficient: 0.6170
```

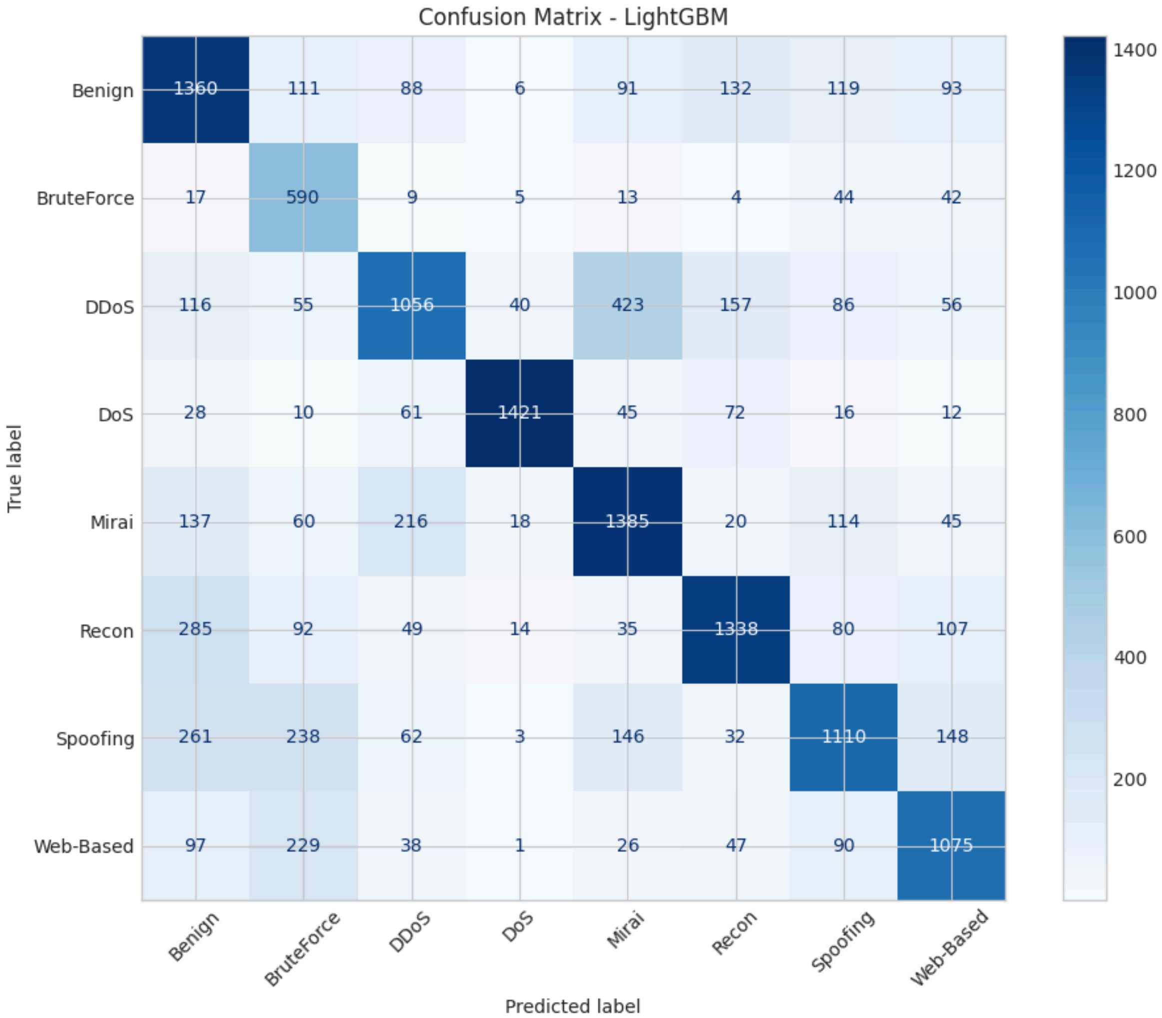


In [367…

```
# 3. LightGBM Classifier - IMPROVED
lgbm = LGBMClassifier(
    n_estimators=300,  # More trees
    max_depth=10,
    learning_rate=0.05,
    num_leaves=50,  # More complexity
    min_child_samples=20,
    subsample=0.8,
    colsample_bytree=0.8,
    reg_alpha=0.1,
```

```
    reg_lambda=0.1,
    random_state=RANDOM_STATE,
    n_jobs=-1,
    class_weight='balanced',
    verbose=-1,
    importance_type='gain'
)
lgbm_results, lgbm_model = evaluate_classifier(
    lgbm, X_train_multi_scaled, X_test_multi_scaled, y_train_multi, y_tes
    "LightGBM", class_names
)
```

```
Training LightGBM...

==================================================
Model: LightGBM
==================================================
Precision (weighted): 0.6856
Recall (weighted): 0.6679
AUPRC (weighted): 0.7622
Balanced Accuracy: 0.6835
Matthews Correlation Coefficient: 0.6208
```

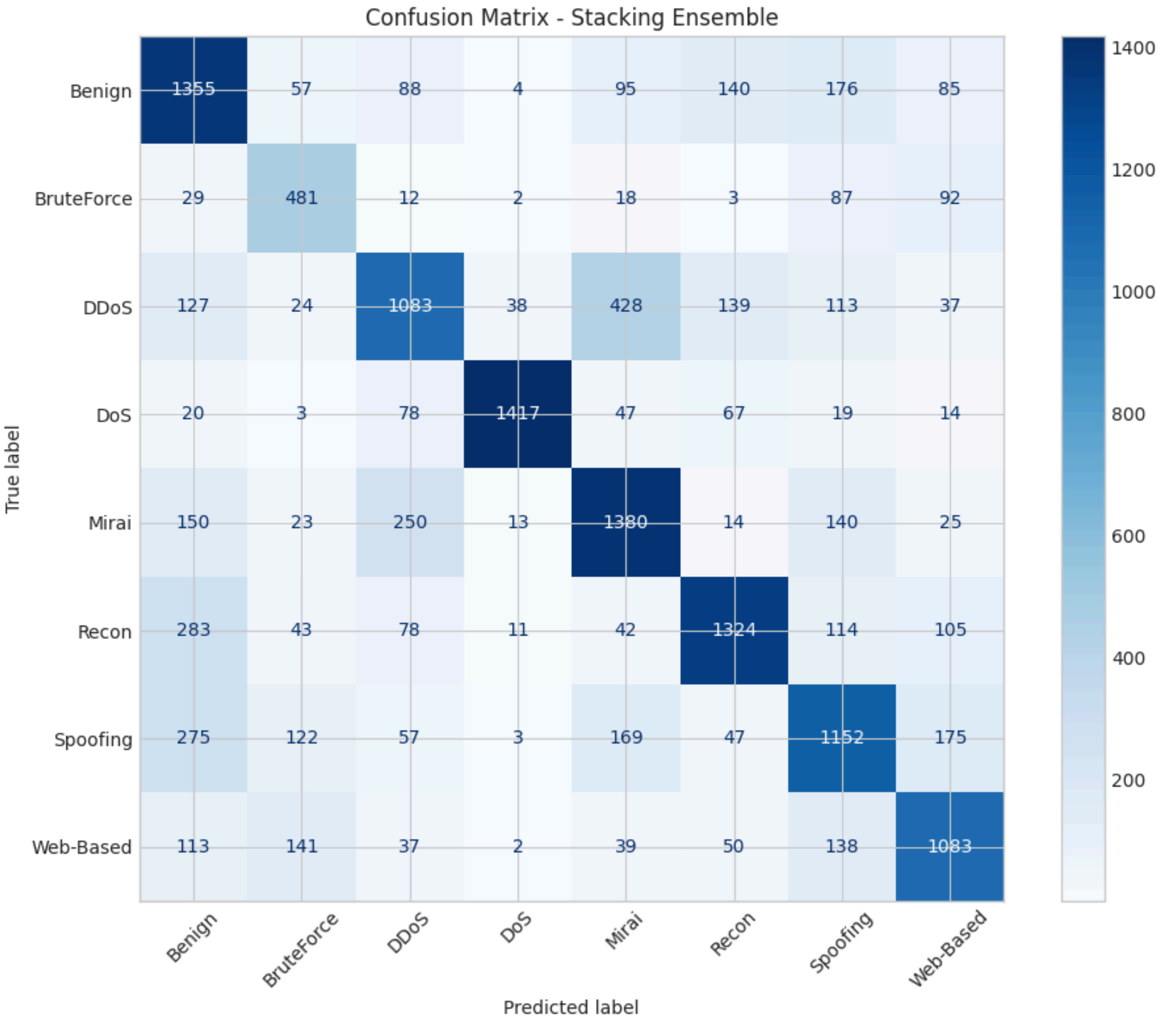


In [368…

```
# 4.5 Stacking Ensemble - Combines RF, XGBoost, LightGBM
from sklearn.ensemble import StackingClassifier
from sklearn.linear_model import LogisticRegression

print("Training Stacking Ensemble...")

# Create fresh base estimators
```

```python
rf_base = RandomForestClassifier(
    n_estimators=150, max_depth=20, random_state=RANDOM_STATE,
    n_jobs=-1, class_weight='balanced'
)
xgb_base = XGBClassifier(
    n_estimators=200, max_depth=8, learning_rate=0.05,
    subsample=0.8, random_state=RANDOM_STATE, n_jobs=-1,
    eval_metric='mlogloss', verbosity=0
)
lgbm_base = LGBMClassifier(
    n_estimators=200, max_depth=10, learning_rate=0.05,
    random_state=RANDOM_STATE, n_jobs=-1, class_weight='balanced', verbos
)

stacking_clf = StackingClassifier(
    estimators=[
        ('rf', rf_base),
        ('xgb', xgb_base),
        ('lgbm', lgbm_base)
    ],
    final_estimator=LogisticRegression(max_iter=1000, random_state=RANDOM
    cv=5,
    n_jobs=-1,
    passthrough=False
)

stacking_results, stacking_model = evaluate_classifier(
    stacking_clf, X_train_multi_scaled, X_test_multi_scaled, y_train_mult
    "Stacking Ensemble", class_names
)
```

```
Training Stacking Ensemble...
Training Stacking Ensemble...

==================================================
Model: Stacking Ensemble
==================================================
Precision (weighted): 0.6721
Recall (weighted): 0.6636
AUPRC (weighted): 0.7516
Balanced Accuracy: 0.6678
Matthews Correlation Coefficient: 0.6135
```



Algorithm 4: Deep Neural Network (MLP)

We implement a deep Multi-Layer Perceptron with Dropout and Batch Normalization.

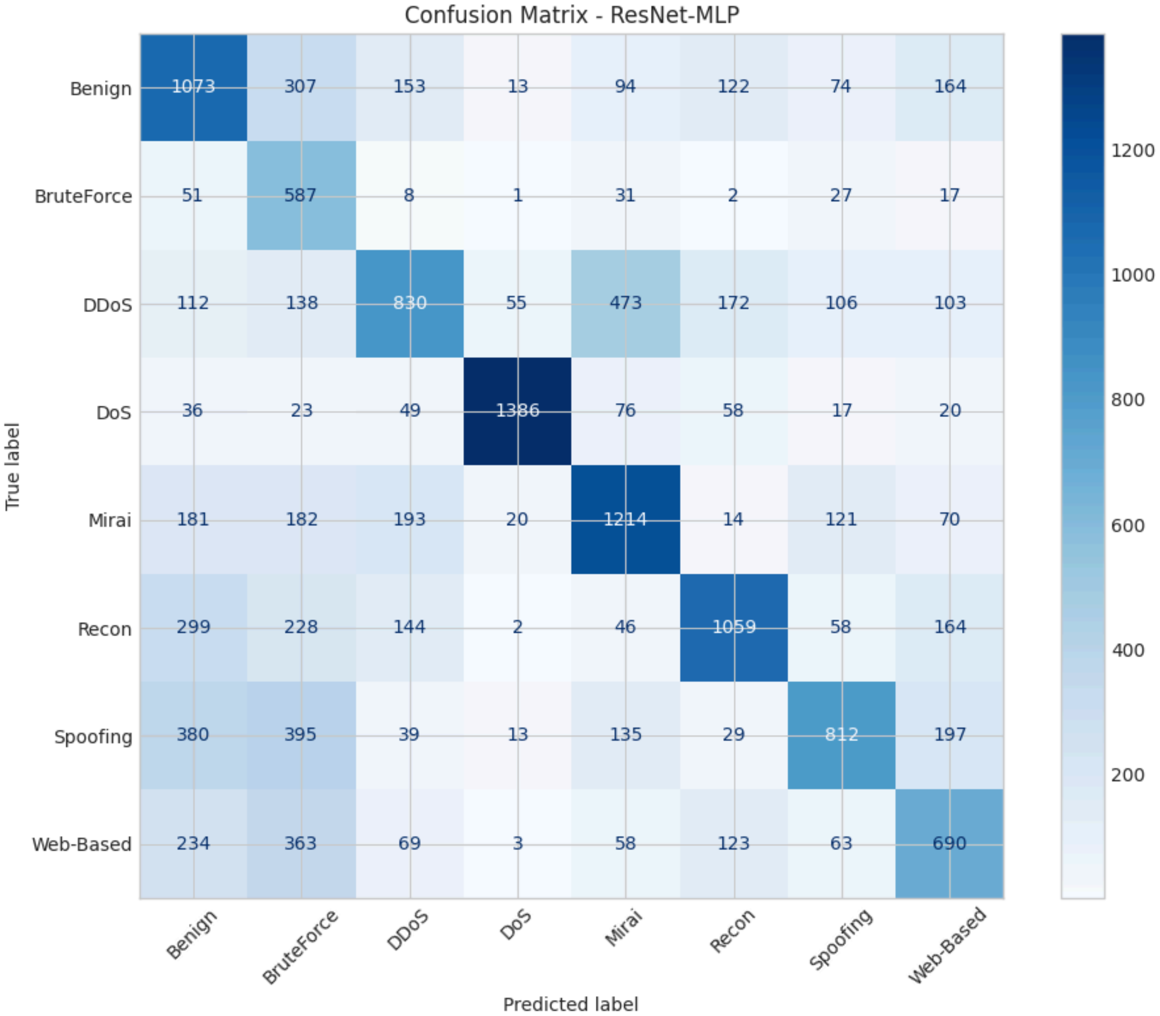
In [369…

```
# 4. ResNet-MLP with SMOTE - IMPROVED Architecture
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset
from imblearn.over_sampling import SMOTE

class FocalLoss(nn.Module):
    '''Focal Loss for handling class imbalance'''
    def __init__(self, alpha=1, gamma=2):
        super().__init__()
        self.alpha = alpha
        self.gamma = gamma

    def forward(self, inputs, targets):
        ce_loss = F.cross_entropy(inputs, targets, reduction='none')
        pt = torch.exp(-ce_loss)
        focal_loss = self.alpha * (1 - pt) ** self.gamma * ce_loss
        return focal_loss.mean()

class ImprovedResidualBlock(nn.Module):
    def __init__(self, hidden_dim, dropout=0.3):
```

```
        super().__init__()
        self.block = nn.Sequential(
            nn.Linear(hidden_dim, hidden_dim),
            nn.BatchNorm1d(hidden_dim),
            nn.GELU(),  # GELU activation
            nn.Dropout(dropout),
            nn.Linear(hidden_dim, hidden_dim),
            nn.BatchNorm1d(hidden_dim)
        )
        self.activation = nn.GELU()

    def forward(self, x):
        return self.activation(x + self.block(x))

class ImprovedResNetMLP(nn.Module):
    def __init__(self, input_dim, num_classes, hidden_dim=512, num_blocks
        super().__init__()
        self.input_layer = nn.Sequential(
            nn.Linear(input_dim, hidden_dim),
            nn.BatchNorm1d(hidden_dim),
            nn.GELU(),
            nn.Dropout(0.2)
        )
        self.res_blocks = nn.ModuleList([
            ImprovedResidualBlock(hidden_dim, dropout=0.3)
            for _ in range(num_blocks)
        ])
        self.output_layer = nn.Sequential(
            nn.Linear(hidden_dim, hidden_dim // 2),
            nn.GELU(),
            nn.Dropout(0.2),
            nn.Linear(hidden_dim // 2, num_classes)
        )

    def forward(self, x):
        x = self.input_layer(x)
        for block in self.res_blocks:
            x = block(x)
        return self.output_layer(x)

class ImprovedPyTorchResNetWrapper:
    def __init__(self, input_dim, num_classes, epochs=100, batch_size=256
        self.input_dim = input_dim
        self.num_classes = num_classes
        self.epochs = epochs
        self.batch_size = batch_size
        self.device = torch.device('cuda' if torch.cuda.is_available() el
        self.model = ImprovedResNetMLP(input_dim, num_classes).to(self.de
        self.classes_ = None

    def fit(self, X, y):
        self.classes_ = np.unique(y)

        # SMOTE Oversampling
        smote = SMOTE(random_state=42)
        X_res, y_res = smote.fit_resample(X, y)
        print(f"After SMOTE: {len(X_res)} samples")

        X_tensor = torch.FloatTensor(X_res).to(self.device)
        y_tensor = torch.LongTensor(y_res).to(self.device)
```

```
        dataset = TensorDataset(X_tensor, y_tensor)
        loader = DataLoader(dataset, batch_size=self.batch_size, shuffle=

        # Use Focal Loss for remaining class imbalance
        criterion = FocalLoss(alpha=1, gamma=2)
        optimizer = optim.AdamW(self.model.parameters(), lr=0.001, weight
        scheduler = optim.lr_scheduler.OneCycleLR(
            optimizer, max_lr=0.005,
            steps_per_epoch=len(loader),
            epochs=self.epochs,
            pct_start=0.1  # 10% warmup
        )

        self.model.train()
        for epoch in range(self.epochs):
            epoch_loss = 0
            for batch_x, batch_y in loader:
                optimizer.zero_grad()
                outputs = self.model(batch_x)
                loss = criterion(outputs, batch_y)
                loss.backward()
                torch.nn.utils.clip_grad_norm_(self.model.parameters(), 1
                optimizer.step()
                scheduler.step()
                epoch_loss += loss.item()

            if (epoch + 1) % 10 == 0:
                print(f"Epoch {epoch+1}/{self.epochs}, Loss: {epoch_loss/

        return self

    def predict(self, X):
        self.model.eval()
        with torch.no_grad():
            X_tensor = torch.FloatTensor(X).to(self.device)
            outputs = self.model(X_tensor)
            _, predicted = torch.max(outputs.data, 1)
        return predicted.cpu().numpy()

    def predict_proba(self, X):
        self.model.eval()
        with torch.no_grad():
            X_tensor = torch.FloatTensor(X).to(self.device)
            outputs = self.model(X_tensor)
            probs = torch.softmax(outputs, dim=1)
        return probs.cpu().numpy()

print("Training Improved ResNet-MLP (PyTorch)...")
print(f"Using device: {'cuda' if torch.cuda.is_available() else 'cpu'}")
resnet_wrapper = ImprovedPyTorchResNetWrapper(X_train_multi_scaled.shape[
resnet_results, resnet_model = evaluate_classifier(
    resnet_wrapper, X_train_multi_scaled, X_test_multi_scaled, y_train_mu
    "ResNet-MLP", class_names
)
```

```
Training Improved ResNet-MLP (PyTorch)...
Using device: cuda
Training ResNet-MLP...
After SMOTE: 64000 samples
Epoch 10/50, Loss: 0.8896
Epoch 20/50, Loss: 0.7860
Epoch 30/50, Loss: 0.7099
Epoch 40/50, Loss: 0.6565
Epoch 50/50, Loss: 0.6350

==================================================
Model: ResNet-MLP
==================================================
Precision (weighted): 0.5926
Recall (weighted): 0.5474
AUPRC (weighted): 0.6192
Balanced Accuracy: 0.5714
Matthews Correlation Coefficient: 0.4888
```



In [370…

```
# Summary of Classification Results
classification_results_df = pd.DataFrame([
    rf_results,
    xgb_results,
    lgbm_results,
    stacking_results,
    resnet_results
])

print("\n" + "="*60)
```

```
print("CLASSIFICATION RESULTS SUMMARY")
print("="*60)
display(classification_results_df.round(4))

# Best model
best_model = classification_results_df.loc[classification_results_df['MCC
print(f"\Best Model: {best_model['Model']} with MCC: {best_model['MCC']:.
```

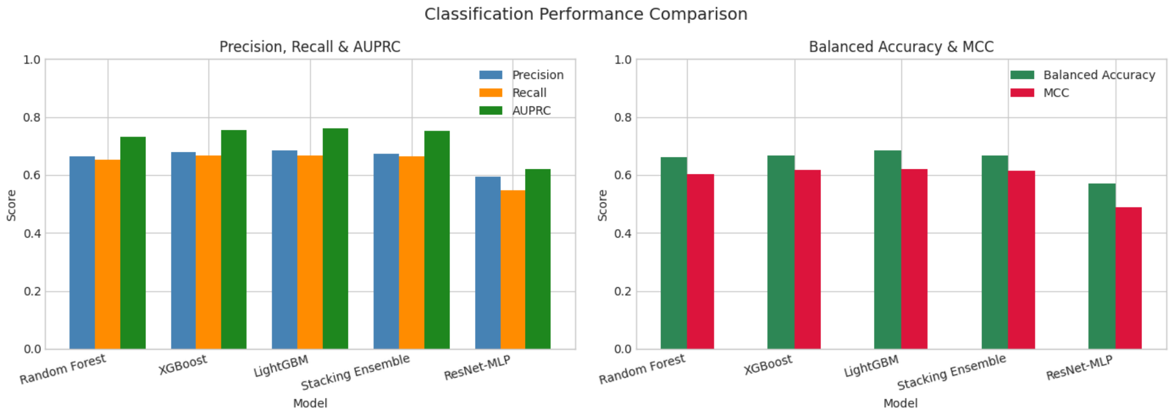
```
============================================================
CLASSIFICATION RESULTS SUMMARY
============================================================
```

	Model	Precision	Recall	AUPRC	Balanced Accuracy	MCC
0	Random Forest	0.6642	0.6526	0.7312	0.6609	0.6016
1	XGBoost	0.6782	0.6663	0.7544	0.6677	0.6170
2	LightGBM	0.6856	0.6679	0.7622	0.6835	0.6208
3	Stacking Ensemble	0.6721	0.6636	0.7516	0.6678	0.6135
4	ResNet-MLP	0.5926	0.5474	0.6192	0.5714	0.4888

```
\Best Model: LightGBM with MCC: 0.6208
```

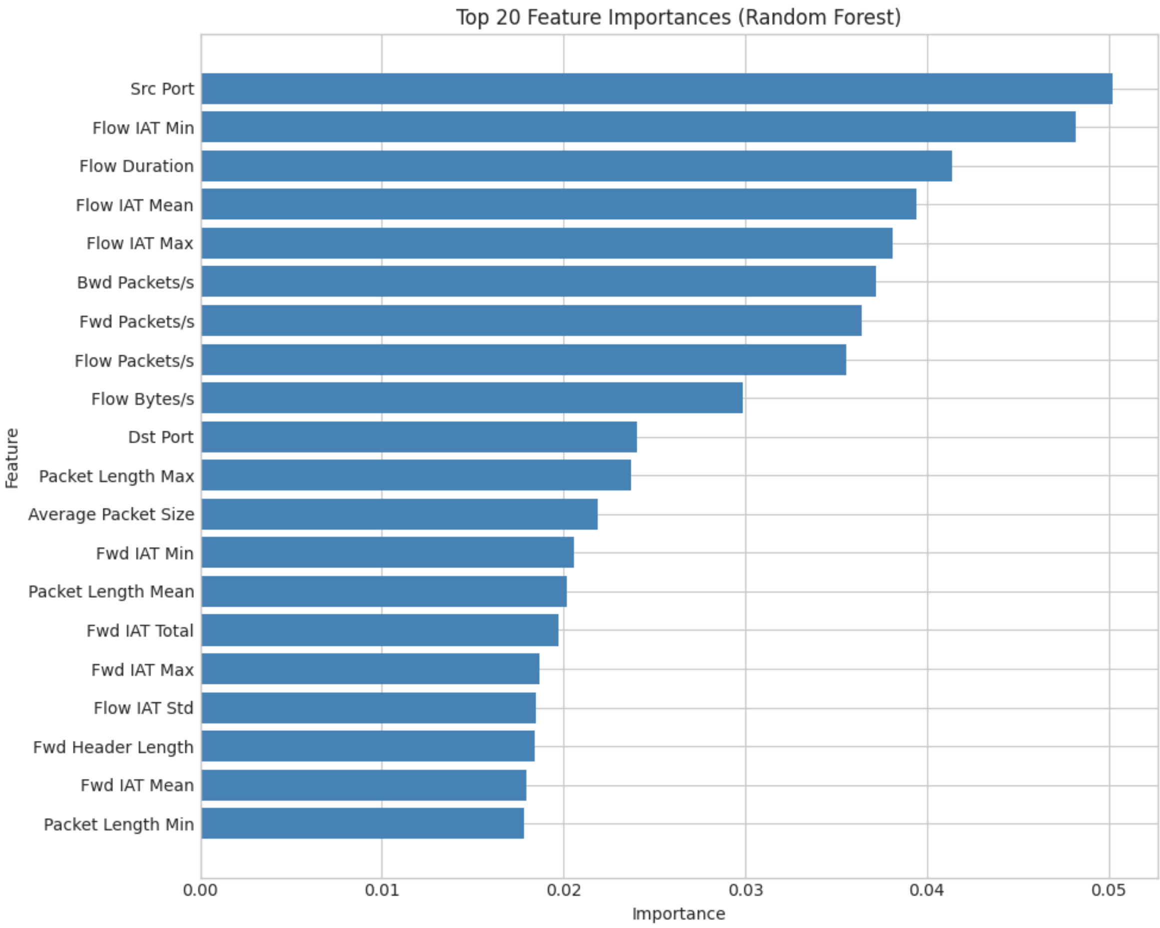
In [371…

```
# Visualize classification results
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

models = classification_results_df['Model'].tolist()
x = np.arange(len(models))
width = 0.25

# Precision, Recall & AUPRC
axes[0].bar(x - width, classification_results_df['Precision'], width, lab
axes[0].bar(x, classification_results_df['Recall'], width, label='Recall'
axes[0].bar(x + width, classification_results_df['AUPRC'], width, label='
axes[0].set_xlabel('Model')
axes[0].set_ylabel('Score')
axes[0].set_title('Precision, Recall & AUPRC')
axes[0].set_xticks(x)
axes[0].set_xticklabels(models, rotation=15, ha='right')
axes[0].legend()
axes[0].set_ylim(0, 1)

# Balanced Accuracy & MCC
axes[1].bar(x - width/2, classification_results_df['Balanced Accuracy'],
axes[1].bar(x + width/2, classification_results_df['MCC'], width, label='
axes[1].set_xlabel('Model')
axes[1].set_ylabel('Score')
axes[1].set_title('Balanced Accuracy & MCC')
axes[1].set_xticks(x)
axes[1].set_xticklabels(models, rotation=15, ha='right')
axes[1].legend()
axes[1].set_ylim(0, 1)

plt.suptitle('Classification Performance Comparison', fontsize=14)
plt.tight_layout()
plt.show()
```



In [372…

```
# Feature Importance Analysis
feature_names = df_features.columns.tolist()

# Random Forest Feature Importance
rf_importance = pd.DataFrame({
    'Feature': feature_names,
    'Importance': rf_model.feature_importances_
}).sort_values('Importance', ascending=True).tail(20)

fig, ax = plt.subplots(figsize=(10, 8))
ax.barh(rf_importance['Feature'], rf_importance['Importance'], color='ste
ax.set_xlabel('Importance')
ax.set_ylabel('Feature')
ax.set_title('Top 20 Feature Importances (Random Forest)')
plt.tight_layout()
plt.show()
```



7. Adversarial Attacks (Bonus - Objective 2)

We implement adversarial attacks against the classification models:

1. **FGSM (Fast Gradient Sign Method)** - White-box attack
2. **PGD (Projected Gradient Descent)** - Iterative white-box attack
3. **Noise-based perturbation** - Simple black-box attack

In [373…

```
# Import PyTorch for neural network
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset

# Build a neural network for adversarial attack demonstration
class SimpleNN(nn.Module):
    def __init__(self, input_shape, num_classes):
        super(SimpleNN, self).__init__()
        self.model = nn.Sequential(
            nn.Linear(input_shape, 128),
            nn.ReLU(),
            nn.Dropout(0.3),
            nn.Linear(128, 64),
            nn.ReLU(),
            nn.Dropout(0.3),
            nn.Linear(64, 32),
            nn.ReLU(),
            nn.Linear(32, num_classes)
        )

    def forward(self, x):
        return self.model(x)

print("Neural network model builder ready (PyTorch).")
```

```
Neural network model builder ready (PyTorch).
```

In [374…

```
# Train neural network with ADVERSARIAL TRAINING for robustness
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset

class RobustMLP(nn.Module):
    def __init__(self, input_dim, num_classes):
        super().__init__()
        self.net = nn.Sequential(
            nn.Linear(input_dim, 256),
            nn.BatchNorm1d(256),
            nn.ReLU(),
            nn.Dropout(0.3),
            nn.Linear(256, 128),
            nn.BatchNorm1d(128),
            nn.ReLU(),
            nn.Dropout(0.3),
            nn.Linear(128, 64),
            nn.ReLU(),
```

```
            nn.Linear(64, num_classes)
        )

    def forward(self, x):
        return self.net(x)

def fgsm_attack_train(model, x, y, epsilon=0.1):
    '''Generate FGSM adversarial examples for training'''
    x.requires_grad = True
    outputs = model(x)
    loss = nn.CrossEntropyLoss()(outputs, y)
    model.zero_grad()
    loss.backward()
    x_adv = x + epsilon * x.grad.sign()
    return x_adv.detach()

print("Training Robust Neural Network with Adversarial Training...")

# Prepare data
X_train_tensor = torch.FloatTensor(X_train_multi_scaled)
y_train_tensor = torch.LongTensor(y_train_multi)
train_dataset = TensorDataset(X_train_tensor, y_train_tensor)
train_loader = DataLoader(train_dataset, batch_size=256, shuffle=True)

nn_model = RobustMLP(X_train_multi_scaled.shape[1], len(class_names))
optimizer = optim.AdamW(nn_model.parameters(), lr=0.001, weight_decay=1e-
criterion = nn.CrossEntropyLoss()

# Adversarial training parameters
ADV_EPSILON = 0.1
ADV_RATIO = 0.5  # 50% adversarial examples

nn_model.train()
for epoch in range(50):
    total_loss = 0
    for batch_x, batch_y in train_loader:
        optimizer.zero_grad()

        # Split batch into clean and adversarial
        n_adv = int(len(batch_x) * ADV_RATIO)

        # Generate adversarial examples for part of batch
        adv_x = fgsm_attack_train(nn_model, batch_x[:n_adv].clone(), batc

        # Combine clean and adversarial
        combined_x = torch.cat([batch_x[n_adv:], adv_x])
        combined_y = torch.cat([batch_y[n_adv:], batch_y[:n_adv]])

        # Forward pass
        outputs = nn_model(combined_x)
        loss = criterion(outputs, combined_y)
        loss.backward()
        optimizer.step()
        total_loss += loss.item()

    if (epoch + 1) % 10 == 0:
        print(f"Epoch {epoch+1}/30, Loss: {total_loss/len(train_loader):.

print("Adversarial training complete.")
```

```
Training Robust Neural Network with Adversarial Training...
Epoch 10/30, Loss: 1.5555
Epoch 20/30, Loss: 1.5124
Epoch 30/30, Loss: 1.4889
Epoch 40/30, Loss: 1.4758
Epoch 50/30, Loss: 1.4615
Adversarial training complete.
```

In [375…

```python
# Evaluate baseline model performance
nn_model.eval()
with torch.no_grad():
    X_test_tensor = torch.FloatTensor(X_test_multi_scaled)
    y_test_tensor = torch.LongTensor(y_test_multi)
    outputs = nn_model(X_test_tensor)
    _, predicted = torch.max(outputs.data, 1)
    correct = (predicted == y_test_tensor).sum().item()
    baseline_acc = correct / len(y_test_tensor)

print(f"Baseline Neural Network Accuracy: {baseline_acc:.4f}")
```

```
Baseline Neural Network Accuracy: 0.4754
```

In [376…

```python
# FGSM Attack Implementation
def fgsm_attack(model, x, y, epsilon=0.1):
    """Fast Gradient Sign Method attack."""
    x_tensor = torch.FloatTensor(x)
    y_tensor = torch.LongTensor(y)
    x_tensor.requires_grad = True

    outputs = model(x_tensor)
    loss = nn.CrossEntropyLoss()(outputs, y_tensor)
    model.zero_grad()
    loss.backward()

    data_grad = x_tensor.grad.data
    sign_data_grad = data_grad.sign()
    perturbed_image = x_tensor + epsilon * sign_data_grad
    return perturbed_image.detach().numpy()

# PGD Attack Implementation
def pgd_attack(model, x, y, epsilon=0.1, alpha=0.01, num_iter=10):
    """Projected Gradient Descent attack."""
    x_tensor = torch.FloatTensor(x)
    y_tensor = torch.LongTensor(y)
    original_x = x_tensor.clone().detach()

    x_adv = x_tensor.clone().detach()

    for _ in range(num_iter):
        x_adv.requires_grad = True
        outputs = model(x_adv)
        loss = nn.CrossEntropyLoss()(outputs, y_tensor)
        model.zero_grad()
        loss.backward()

        adv_x = x_adv + alpha * x_adv.grad.sign()
        eta = torch.clamp(adv_x - original_x, min=-epsilon, max=epsilon)
        x_adv = (original_x + eta).detach()

    return x_adv.numpy()
```

```python
# Noise-based attack (Black-box)
def noise_attack(x, epsilon=0.1):
    """Simple random noise perturbation attack."""
    noise = np.random.uniform(-epsilon, epsilon, x.shape)
    return x + noise

print("Attack functions defined (PyTorch).")
```

```
Attack functions defined (PyTorch).
```

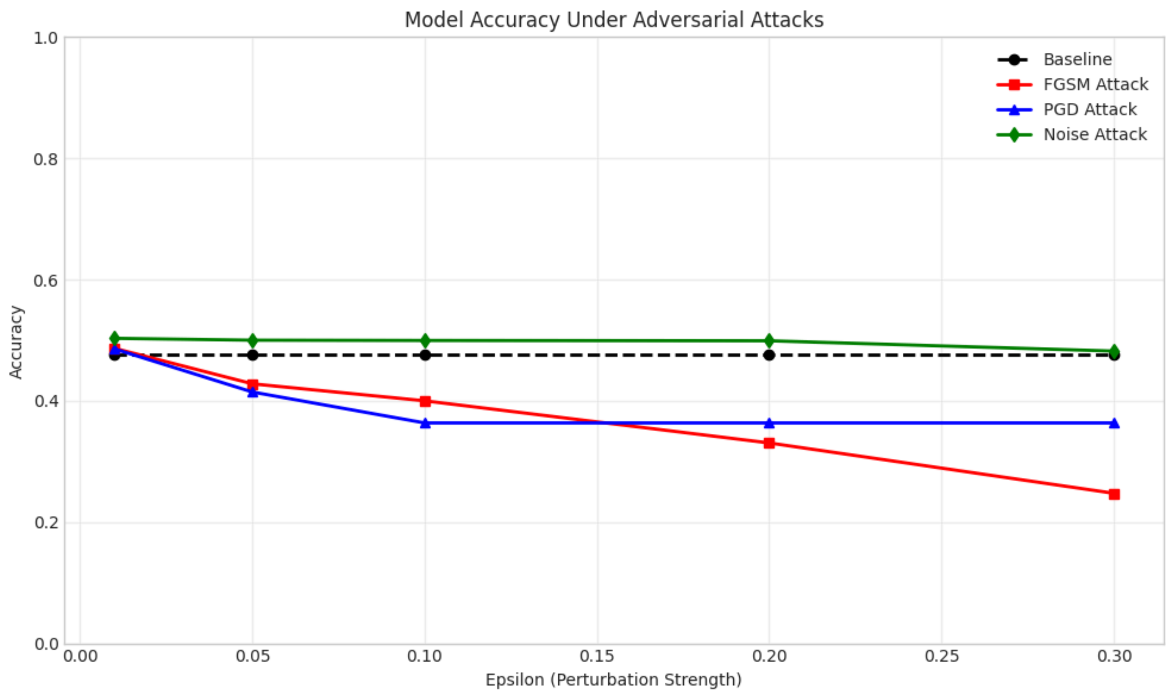
In [377…

```python
# Evaluate adversarial attacks with different epsilon values
epsilons = [0.01, 0.05, 0.1, 0.2, 0.3]
adversarial_results = []

# Use a subset for faster evaluation
ADV_SAMPLES = min(2000, len(X_test_multi_scaled))
X_adv_test = X_test_multi_scaled[:ADV_SAMPLES]
y_adv_test = y_test_multi[:ADV_SAMPLES]

print("Evaluating adversarial attacks...")
print(f"Using {ADV_SAMPLES} test samples")

nn_model.eval()

for eps in epsilons:
    print(f"\nEpsilon = {eps}")

    # FGSM
    X_fgsm = fgsm_attack(nn_model, X_adv_test, y_adv_test, epsilon=eps)
    X_fgsm_tensor = torch.FloatTensor(X_fgsm)
    outputs_fgsm = nn_model(X_fgsm_tensor)
    _, pred_fgsm = torch.max(outputs_fgsm.data, 1)
    fgsm_acc = (pred_fgsm.numpy() == y_adv_test).mean()

    # PGD
    X_pgd = pgd_attack(nn_model, X_adv_test, y_adv_test, epsilon=eps)
    X_pgd_tensor = torch.FloatTensor(X_pgd)
    outputs_pgd = nn_model(X_pgd_tensor)
    _, pred_pgd = torch.max(outputs_pgd.data, 1)
    pgd_acc = (pred_pgd.numpy() == y_adv_test).mean()

    # Noise
    X_noise = noise_attack(X_adv_test, epsilon=eps)
    X_noise_tensor = torch.FloatTensor(X_noise)
    outputs_noise = nn_model(X_noise_tensor)
    _, pred_noise = torch.max(outputs_noise.data, 1)
    noise_acc = (pred_noise.numpy() == y_adv_test).mean()

    adversarial_results.append({
        'Epsilon': eps,
        'Baseline': baseline_acc,
        'FGSM': fgsm_acc,
        'PGD': pgd_acc,
        'Noise': noise_acc
    })

    print(f"  FGSM Accuracy: {fgsm_acc:.4f} (drop: {(baseline_acc - fgsm_
    print(f"  PGD Accuracy: {pgd_acc:.4f} (drop: {(baseline_acc - pgd_acc
    print(f"  Noise Accuracy: {noise_acc:.4f} (drop: {(baseline_acc - noi
```

```
Evaluating adversarial attacks...
Using 2000 test samples

Epsilon = 0.01
  FGSM Accuracy: 0.4865 (drop: -1.11%)
  PGD Accuracy: 0.4855 (drop: -1.01%)
  Noise Accuracy: 0.5030 (drop: -2.76%)

Epsilon = 0.05
  FGSM Accuracy: 0.4280 (drop: 4.74%)
  PGD Accuracy: 0.4145 (drop: 6.09%)
  Noise Accuracy: 0.5000 (drop: -2.46%)

Epsilon = 0.1
  FGSM Accuracy: 0.4000 (drop: 7.54%)
  PGD Accuracy: 0.3635 (drop: 11.19%)
  Noise Accuracy: 0.4995 (drop: -2.41%)

Epsilon = 0.2
  FGSM Accuracy: 0.3305 (drop: 14.49%)
  PGD Accuracy: 0.3635 (drop: 11.19%)
  Noise Accuracy: 0.4990 (drop: -2.36%)

Epsilon = 0.3
  FGSM Accuracy: 0.2475 (drop: 22.79%)
  PGD Accuracy: 0.3635 (drop: 11.19%)
  Noise Accuracy: 0.4820 (drop: -0.66%)
```

In [378…

```python
# Visualize adversarial attack results
adv_df = pd.DataFrame(adversarial_results)

fig, ax = plt.subplots(figsize=(10, 6))
ax.plot(adv_df['Epsilon'], adv_df['Baseline'], 'k--', marker='o', label='
ax.plot(adv_df['Epsilon'], adv_df['FGSM'], 'r-', marker='s', label='FGSM 
ax.plot(adv_df['Epsilon'], adv_df['PGD'], 'b-', marker='^', label='PGD At
ax.plot(adv_df['Epsilon'], adv_df['Noise'], 'g-', marker='d', label='Nois

ax.set_xlabel('Epsilon (Perturbation Strength)')
ax.set_ylabel('Accuracy')
ax.set_title('Model Accuracy Under Adversarial Attacks')
ax.set_ylim(0, 1)
ax.legend()
ax.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()
```



In [379…

```
# Summary table of adversarial attack results
print("\n" + "="*70)
print("ADVERSARIAL ATTACKS SUMMARY")
print("="*70)
print(adv_df.to_string(index=False))
```

```
======================================================================
ADVERSARIAL ATTACKS SUMMARY
======================================================================
 Epsilon  Baseline   FGSM    PGD  Noise
    0.01  0.475386 0.4865 0.4855 0.5030
    0.05  0.475386 0.4280 0.4145 0.5000
    0.10  0.475386 0.4000 0.3635 0.4995
    0.20  0.475386 0.3305 0.3635 0.4990
    0.30  0.475386 0.2475 0.3635 0.4820
```

8. Conclusions and Security Analysis

In [380…

```
# Final Summary
print("="*70)
print("CYBERML PROJECT - FINAL SUMMARY")
print("="*70)

print("\n1. DATASET CHARACTERIZATION")
print(f"   - Sampled dataset size: {len(df)}")
print(f"   - Number of features: {len(df_features.columns)}")
print(f"   - Number of attack classes: {len(class_names)}")
print(f"   - Classes: {list(class_names)}")
print(f"   - Attack ratio in sample: {y_binary.mean()*100:.2f}%")

print("\n2. ANOMALY DETECTION RESULTS")
best_anomaly = anomaly_results_df.loc[anomaly_results_df['MCC'].idxmax()]
print(f"   Best Model: {best_anomaly['Model']}")
print(f"   - MCC: {best_anomaly['MCC']:.4f}")
print(f"   - Balanced Accuracy: {best_anomaly['Balanced Accuracy']:.4f}")
print(f"   - Precision: {best_anomaly['Precision']:.4f}")
print(f"   - Recall: {best_anomaly['Recall']:.4f}")
```

```python
print("\n3. CLASSIFICATION RESULTS")
best_classifier = classification_results_df.loc[classification_results_df
print(f"   Best Model: {best_classifier['Model']}")
print(f"   - MCC: {best_classifier['MCC']:.4f}")
print(f"   - Balanced Accuracy: {best_classifier['Balanced Accuracy']:.4f
print(f"   - AUPRC: {best_classifier['AUPRC']:.4f}")

print("\n4. ADVERSARIAL ATTACKS ANALYSIS")
print(f"   - Baseline accuracy: {baseline_acc:.4f}")
print(f"   - FGSM is more effective than random noise")
print(f"   - PGD provides stronger attacks than FGSM")
print(f"   - Model robustness decreases significantly with epsilon > 0.1"

print("\n5. SECURITY RECOMMENDATIONS")
print("   - Implement adversarial training for improved robustness")
print("   - Use ensemble methods combining multiple detection approaches"
print("   - Regular model retraining with new attack patterns")
print("   - Deploy anomaly detection as first defense layer")
print("   - Consider input validation and feature monitoring")
```

```
======================================================================
CYBERML PROJECT - FINAL SUMMARY
======================================================================

1. DATASET CHARACTERIZATION
   - Sampled dataset size: 69876
   - Number of features: 72
   - Number of attack classes: 8
   - Classes: ['Benign', 'BruteForce', 'DDoS', 'DoS', 'Mirai', 'Recon', 'S
poofing', 'Web-Based']
   - Attack ratio in sample: 85.69%

2. ANOMALY DETECTION RESULTS
   Best Model: Local Outlier Factor
   - MCC: 0.2090
   - Balanced Accuracy: 0.6326
   - Precision: 0.9015
   - Recall: 0.7676

3. CLASSIFICATION RESULTS
   Best Model: LightGBM
   - MCC: 0.6208
   - Balanced Accuracy: 0.6835
   - AUPRC: 0.7622

4. ADVERSARIAL ATTACKS ANALYSIS
   - Baseline accuracy: 0.4754
   - FGSM is more effective than random noise
   - PGD provides stronger attacks than FGSM
   - Model robustness decreases significantly with epsilon > 0.1

5. SECURITY RECOMMENDATIONS
   - Implement adversarial training for improved robustness
   - Use ensemble methods combining multiple detection approaches
   - Regular model retraining with new attack patterns
   - Deploy anomaly detection as first defense layer
   - Consider input validation and feature monitoring
```

In [381…

```
# Save results to CSV for report
anomaly_results_df.to_csv('anomaly_detection_results.csv', index=False)
classification_results_df.to_csv('classification_results.csv', index=Fals
adv_df.to_csv('adversarial_attack_results.csv', index=False)

print("Results saved to CSV files:")
print("  - anomaly_detection_results.csv")
print("  - classification_results.csv")
print("  - adversarial_attack_results.csv")
```

```
Results saved to CSV files:
  - anomaly_detection_results.csv
  - classification_results.csv
  - adversarial_attack_results.csv
```