baselines_model

May 17, 2025

[18]:
```
# Baseline Model Training Focused on Malware Detection

# === 0. Imports and Setup ===
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import joblib
import os
import torch
import warnings
from sklearn.model_selection import train_test_split, KFold, cross_validate
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.metrics import (
    accuracy_score, f1_score, recall_score, precision_score,
    roc_auc_score, classification_report, confusion_matrix
)
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
import xgboost as xgb
import lightgbm as lgb
```

[19]:
```
warnings.filterwarnings("ignore", category=UserWarning)
SEED = 42
np.random.seed(SEED)
torch.manual_seed(SEED)

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
```

[20]:
```
import pandas as pd
df = pd.read_csv('/home/nhat/projectcuoiky/data/pdf_features.csv')
```

[21]:
```
print("Shape of DataFrame:", df.shape)
print("Columns in DataFrame:", df.columns.tolist())
```

```
Shape of DataFrame: (11101, 25)
Columns in DataFrame: ['Page', 'Encrypt', 'ObjStm', 'JS', 'JavaScript', 'AA',
'OpenAction', 'AcroForm', 'JBIG2Decode', 'RichMedia', 'Launch', 'EmbeddedFile',
```

```
'XFA', 'Colors_gt_224', 'obj', 'endobj', 'stream', 'endstream', 'xref',
'trailer', 'startxref', 'filepath', 'filename', 'filesize_kb', 'label']
```

[22]:
```python
# Display basic info about the data
print("DataFrame shape:", df.shape)
print("\nFirst few rows of the data:")
print(df.head())

# Check if 'label' column exists
if 'label' in df.columns:
    # Create label encoder and transform the 'label' column
    le = LabelEncoder()
    df['label_numeric'] = le.fit_transform(df['label'])

    # Prepare features (X) and target (y)
    X = df.drop(columns=['label_numeric', 'label'])
    y = df['label_numeric']

    print("\nLabel encoding completed successfully!")
    print("Unique labels:", df['label'].unique())
    print("Label mapping:", dict(zip(le.classes_, range(len(le.classes_)))))
else:
    print("Error: 'label' column not found in the DataFrame.")
    print("Available columns:", df.columns.tolist())
```

```
DataFrame shape: (11101, 25)

First few rows of the data:
   Page  Encrypt  ObjStm  JS  JavaScript  AA  OpenAction  AcroForm  \
0     1        0       0   0           0   0           0         0
1     1        0       0   0           0   0           0         0
2     4        0       6   0           0   0           0         0
3     1        0       0   0           0   0           0         1
4     6        0      25   0           0   0           0         2

   JBIG2Decode  RichMedia  …  endobj  stream  endstream  xref  trailer  \
0            0          0  …      11       3          3     2        2
1            0          0  …       6       2          2     1        1
2            0          0  …      56      41         41     0        0
3            0          0  …      29      17         17     2        2
4            0          0  …     156     146        146     0        0

   startxref                                           filepath  \
0          2  /home/remnux/Desktop/extraction/data/Benign/as…
1          1  /home/remnux/Desktop/extraction/data/Benign/ar…
2          3  /home/remnux/Desktop/extraction/data/Benign/p4…
3          2  /home/remnux/Desktop/extraction/data/Benign/ar…
4          4  /home/remnux/Desktop/extraction/data/Benign/f9…
```

```
           filename  filesize_kb   label
0         assehc.pdf    23.120117  benign
1      artauthor.pdf    69.544922  benign
2       p4894_ru.pdf   180.786133  benign
3   artisticwall.pdf    85.124023  benign
4         f990sn.pdf   126.099609  benign

[5 rows x 25 columns]

Label encoding completed successfully!
Unique labels: ['benign' 'malicious']
Label mapping: {'benign': 0, 'malicious': 1}
```

[23]:
```
# Drop non-numeric columns (including label, filepath, filename)
X = df.drop(columns=['label', 'label_numeric', 'filepath', 'filename'])
y = df['label_numeric']

# Split into train/test sets
X_train_df, X_test_df, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=42, stratify=y
)
```

[24]:
```
# Standard scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_df)
X_test_scaled = scaler.transform(X_test_df)
```

[25]:
```
# === 3. Define MLP Model ===
class SimpleMLP(torch.nn.Module):
    def __init__(self, input_dim, hidden_dim1, hidden_dim2, output_dim):
        super(SimpleMLP, self).__init__()
        self.fc1 = torch.nn.Linear(input_dim, hidden_dim1)
        self.relu1 = torch.nn.ReLU()
        self.dropout1 = torch.nn.Dropout(0.3)
        self.fc2 = torch.nn.Linear(hidden_dim1, hidden_dim2)
        self.relu2 = torch.nn.ReLU()
        self.dropout2 = torch.nn.Dropout(0.3)
        self.fc3 = torch.nn.Linear(hidden_dim2, output_dim)

    def forward(self, x):
        x = self.relu1(self.fc1(x))
        x = self.dropout1(x)
        x = self.relu2(self.fc2(x))
        x = self.dropout2(x)
        x = self.fc3(x)
        return x
```

```python
def get_pytorch_predictions(model, X_data, threshold=0.5):
    model.eval()
    with torch.no_grad():
        X_tensor = torch.FloatTensor(X_data).to(device)
        outputs = model(X_tensor)
        probas = torch.sigmoid(outputs).cpu().numpy().flatten()
        preds = (probas > threshold).astype(int)
    return preds, probas
```

[26]:
```python
# === 4. Cross-Validation Training Functions ===
def cv_train_evaluate(model_class, model_params, X_data, y_data):
    scoring = ['accuracy', 'precision', 'recall', 'f1', 'roc_auc']
    model = model_class(**model_params)
    kfold = KFold(n_splits=5, shuffle=True, random_state=SEED)
    results = cross_validate(model, X_data, y_data, scoring=scoring, cv=kfold,␣
↪return_train_score=True)
    model.fit(X_data, y_data)
    return model, results

def cv_train_evaluate_mlp(input_dim, hidden_dim1, hidden_dim2, X_train_data,␣
↪y_train_data, epochs=50, batch_size=64):
    kfold = KFold(n_splits=5, shuffle=True, random_state=SEED)
    results = []
    for train_idx, val_idx in kfold.split(X_train_data):
        X_train, X_val = X_train_data[train_idx], X_train_data[val_idx]
        y_train, y_val = y_train_data[train_idx], y_train_data[val_idx]

        model = SimpleMLP(input_dim, hidden_dim1, hidden_dim2, 1).to(device)
        criterion = torch.nn.BCEWithLogitsLoss(pos_weight=torch.tensor([4.0]).
↪to(device))
        optimizer = torch.optim.Adam(model.parameters(), lr=0.001)

        for epoch in range(epochs):
            model.train()
            permutation = torch.randperm(X_train.shape[0])
            for i in range(0, X_train.shape[0], batch_size):
                indices = permutation[i:i+batch_size]
                X_batch = torch.FloatTensor(X_train[indices]).to(device)
                y_batch = torch.FloatTensor(y_train[indices]).unsqueeze(1).
↪to(device)
                optimizer.zero_grad()
                output = model(X_batch)
                loss = criterion(output, y_batch)
                loss.backward()
                optimizer.step()
```

```
        preds, probs = get_pytorch_predictions(model, X_val, threshold=0.4)
        results.append({
            'accuracy': accuracy_score(y_val, preds),
            'precision': precision_score(y_val, preds),
            'recall': recall_score(y_val, preds),
            'f1': f1_score(y_val, preds),
            'roc_auc': roc_auc_score(y_val, probs)
        })

    return model, results
```

[27]:
```
# === Utility: Threshold Tuning ===
def tune_thresholds(y_true, y_probs, model_name):
    thresholds = np.linspace(0.0, 1.0, 101)
    f1s, recalls = [], []
    for t in thresholds:
        preds = (y_probs >= t).astype(int)
        f1s.append(f1_score(y_true, preds))
        recalls.append(recall_score(y_true, preds))

    best_idx = np.argmax(f1s)
    best_threshold = thresholds[best_idx]

    plt.figure(figsize=(7, 5))
    plt.plot(thresholds, f1s, label="F1 Score")
    plt.plot(thresholds, recalls, label="Recall")
    plt.axvline(best_threshold, color='r', linestyle='--', label=f"Best␣
↪Threshold = {best_threshold:.2f}")
    plt.title(f"Threshold Tuning for {model_name}")
    plt.xlabel("Threshold")
    plt.ylabel("Score")
    plt.legend()
    plt.grid(True)
    plt.tight_layout()
    plt.show()

    print(f"Optimal threshold for {model_name} = {best_threshold:.2f} with F1 =␣
↪{f1s[best_idx]:.4f} and Recall = {recalls[best_idx]:.4f}")
    return best_threshold
```

[28]:
```
# === Utility: Apply Threshold During Training ===
def train_model_with_threshold(model_class, model_params, X_train, y_train,␣
↪X_val, y_val, threshold=0.5):
    model = model_class(**model_params)
    model.fit(X_train, y_train)

    # Get probability predictions
```

```python
    y_probs = model.predict_proba(X_val)[:, 1]

    # Apply threshold
    y_pred = (y_probs > threshold).astype(int)

    # Calculate metrics with applied threshold
    accuracy = accuracy_score(y_val, y_pred)
    precision = precision_score(y_val, y_pred)
    recall = recall_score(y_val, y_pred)
    f1 = f1_score(y_val, y_pred)
    auc = roc_auc_score(y_val, y_probs)

    print(f"Metrics with threshold {threshold:.2f}:")
    print(f"  Accuracy: {accuracy:.4f}")
    print(f"  Precision: {precision:.4f}")
    print(f"  Recall: {recall:.4f}")
    print(f"  F1 Score: {f1:.4f}")
    print(f"  ROC AUC: {auc:.4f}")

    return model, {
        'accuracy': accuracy,
        'precision': precision,
        'recall': recall,
        'f1': f1,
        'roc_auc': auc
    }

def train_mlp_with_threshold(input_dim, hidden_dim1, hidden_dim2, X_train, y_train, X_val, y_val, threshold=0.4, epochs=50, batch_size=64):
    model = SimpleMLP(input_dim, hidden_dim1, hidden_dim2, 1).to(device)
    criterion = torch.nn.BCEWithLogitsLoss(pos_weight=torch.tensor([4.0]).to(device))
    optimizer = torch.optim.Adam(model.parameters(), lr=0.001)

    for epoch in range(epochs):
        model.train()
        permutation = torch.randperm(X_train.shape[0])
        for i in range(0, X_train.shape[0], batch_size):
            indices = permutation[i:i+batch_size]
            X_batch = torch.FloatTensor(X_train[indices]).to(device)
            y_batch = torch.FloatTensor(y_train[indices]).unsqueeze(1).to(device)
            optimizer.zero_grad()
            output = model(X_batch)
            loss = criterion(output, y_batch)
            loss.backward()
            optimizer.step()
```

```python
    # Apply threshold
    preds, probs = get_pytorch_predictions(model, X_val, threshold)

    # Calculate metrics
    accuracy = accuracy_score(y_val, preds)
    precision = precision_score(y_val, preds)
    recall = recall_score(y_val, preds)
    f1 = f1_score(y_val, preds)
    auc = roc_auc_score(y_val, probs)

    print(f"MLP Metrics with threshold {threshold:.2f}:")
    print(f"  Accuracy: {accuracy:.4f}")
    print(f"  Precision: {precision:.4f}")
    print(f"  Recall: {recall:.4f}")
    print(f"  F1 Score: {f1:.4f}")
    print(f"  ROC AUC: {auc:.4f}")

    return model, {
        'accuracy': accuracy,
        'precision': precision,
        'recall': recall,
        'f1': f1,
        'roc_auc': auc
    }
```

[29]:
```python
# === 5. Train Models with Optimal Thresholds ===
# Define the optimal thresholds
svm_threshold = 0.59
rf_threshold = 0.46
xgb_threshold = 0.66
lgb_threshold = 0.83
mlp_threshold = 0.71

print("Training SVM with threshold =", svm_threshold)
svm_model, svm_metrics = train_model_with_threshold(
    SVC,
    {'probability': True, 'random_state': SEED, 'class_weight': 'balanced'},
    X_train_scaled, y_train, X_test_scaled, y_test, threshold=svm_threshold
)

print("\nTraining Random Forest with threshold =", rf_threshold)
rf_model, rf_metrics = train_model_with_threshold(
    RandomForestClassifier,
    {'random_state': SEED, 'class_weight': 'balanced'},
    X_train_df, y_train, X_test_df, y_test, threshold=rf_threshold
)
```

```python
print("\nTraining XGBoost with threshold =", xgb_threshold)
xgb_model, xgb_metrics = train_model_with_threshold(
    xgb.XGBClassifier,
    {'use_label_encoder': False, 'eval_metric': 'logloss', 'random_state':␣
 ↪SEED, 'scale_pos_weight': 4.0},
    X_train_df, y_train, X_test_df, y_test, threshold=xgb_threshold
)

print("\nTraining LightGBM with threshold =", lgb_threshold)
lgb_model, lgb_metrics = train_model_with_threshold(
    lgb.LGBMClassifier,
    {'random_state': SEED, 'scale_pos_weight': 4.0},
    X_train_df, y_train, X_test_df, y_test, threshold=lgb_threshold
)

print("\nTraining MLP with threshold =", mlp_threshold)
mlp_model, mlp_metrics = train_mlp_with_threshold(
    X_train_scaled.shape[1], 128, 64,
    X_train_scaled, y_train.to_numpy(),
    X_test_scaled, y_test.to_numpy(),
    threshold=mlp_threshold
)

# Display comparative metrics
models_metrics = {
    'SVM': svm_metrics,
    'Random Forest': rf_metrics,
    'XGBoost': xgb_metrics,
    'LightGBM': lgb_metrics,
    'MLP': mlp_metrics
}

# Convert to DataFrame for cleaner visualization
metrics_df = pd.DataFrame(models_metrics).T
print("\n=== Summary of Model Performance with Optimal Thresholds ===")
print(metrics_df)
```

```
Training SVM with threshold = 0.59
Metrics with threshold 0.59:
  Accuracy: 0.9730
  Precision: 0.9774
  Recall: 0.8696
  F1 Score: 0.9204
  ROC AUC: 0.9776

Training Random Forest with threshold = 0.46
Metrics with threshold 0.59:
```

```
  Accuracy: 0.9730
  Precision: 0.9774
  Recall: 0.8696
  F1 Score: 0.9204
  ROC AUC: 0.9776

Training Random Forest with threshold = 0.46
Metrics with threshold 0.46:
  Accuracy: 0.9880
  Precision: 0.9777
  Recall: 0.9548
  F1 Score: 0.9662
  ROC AUC: 0.9970

Training XGBoost with threshold = 0.66
Metrics with threshold 0.66:
  Accuracy: 0.9907
  Precision: 0.9781
  Recall: 0.9699
  F1 Score: 0.9740
  ROC AUC: 0.9981

Training LightGBM with threshold = 0.83
[LightGBM] [Info] Number of positive: 1396, number of negative: 6374
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.000302 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 1498
[LightGBM] [Info] Number of data points in the train set: 7770, number of used
features: 21
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.179665 -> initscore=-1.518616
[LightGBM] [Info] Start training from score -1.518616
Metrics with threshold 0.83:
  Accuracy: 0.9898
  Precision: 0.9829
  Recall: 0.9599
  F1 Score: 0.9712
  ROC AUC: 0.9979

Training MLP with threshold = 0.71
Metrics with threshold 0.46:
  Accuracy: 0.9880
  Precision: 0.9777
  Recall: 0.9548
  F1 Score: 0.9662
  ROC AUC: 0.9970
```

```
Training XGBoost with threshold = 0.66
Metrics with threshold 0.66:
  Accuracy: 0.9907
  Precision: 0.9781
  Recall: 0.9699
  F1 Score: 0.9740
  ROC AUC: 0.9981

Training LightGBM with threshold = 0.83
[LightGBM] [Info] Number of positive: 1396, number of negative: 6374
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of
testing was 0.000302 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 1498
[LightGBM] [Info] Number of data points in the train set: 7770, number of used
features: 21
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.179665 -> initscore=-1.518616
[LightGBM] [Info] Start training from score -1.518616
Metrics with threshold 0.83:
  Accuracy: 0.9898
  Precision: 0.9829
  Recall: 0.9599
  F1 Score: 0.9712
  ROC AUC: 0.9979

Training MLP with threshold = 0.71
MLP Metrics with threshold 0.71:
  Accuracy: 0.9829
  Precision: 0.9501
  Recall: 0.9548
  F1 Score: 0.9525
  ROC AUC: 0.9923

=== Summary of Model Performance with Optimal Thresholds ===
               accuracy  precision    recall        f1   roc_auc
SVM            0.972981   0.977444  0.869565  0.920354  0.977647
Random Forest  0.987992   0.977740  0.954849  0.966159  0.996982
XGBoost        0.990693   0.978078  0.969900  0.973971  0.998078
LightGBM       0.989793   0.982877  0.959866  0.971235  0.997880
MLP            0.982888   0.950083  0.954849  0.952460  0.992327
MLP Metrics with threshold 0.71:
  Accuracy: 0.9829
  Precision: 0.9501
  Recall: 0.9548
  F1 Score: 0.9525
  ROC AUC: 0.9923
```

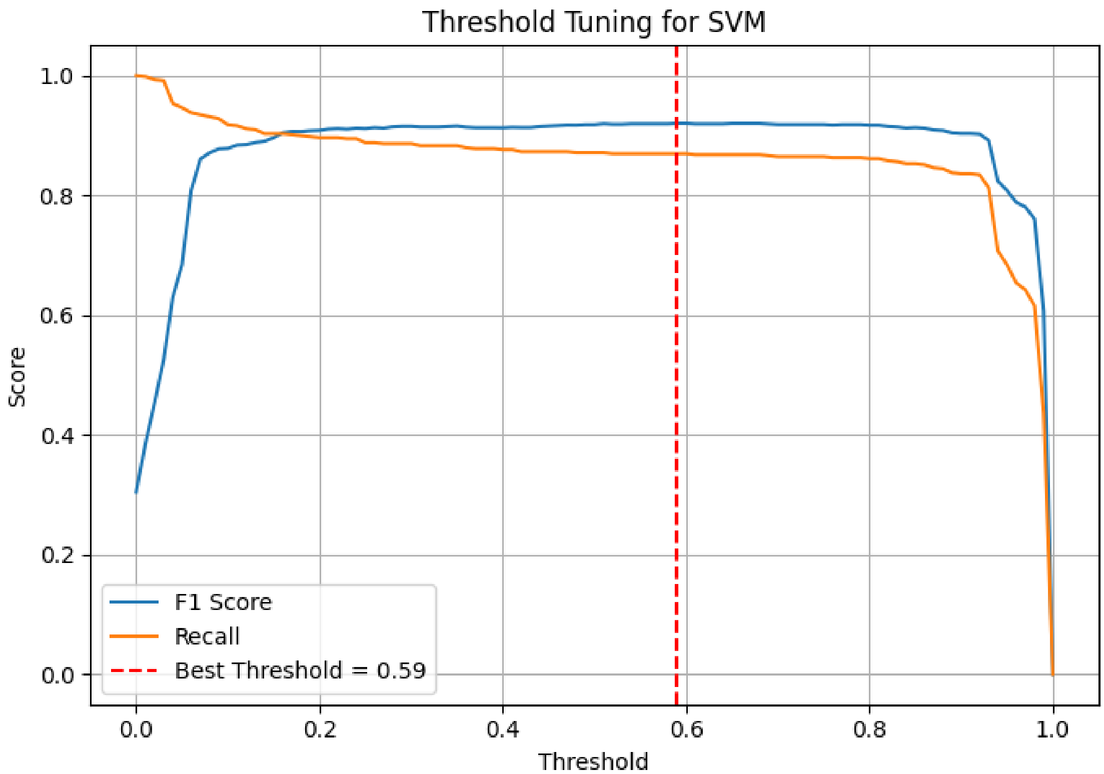
```
=== Summary of Model Performance with Optimal Thresholds ===
               accuracy  precision    recall        f1   roc_auc
SVM            0.972981   0.977444  0.869565  0.920354  0.977647
Random Forest  0.987992   0.977740  0.954849  0.966159  0.996982
XGBoost        0.990693   0.978078  0.969900  0.973971  0.998078
LightGBM       0.989793   0.982877  0.959866  0.971235  0.997880
MLP            0.982888   0.950083  0.954849  0.952460  0.992327
```

[30]:
```
# === Save Models ===
import os
os.makedirs("models", exist_ok=True)
joblib.dump(svm_model, "/home/nhat/projectcuoiky/models/svm_baseline.joblib")
joblib.dump(rf_model, "/home/nhat/projectcuoiky/models/rf_baseline.joblib")
joblib.dump(xgb_model, "/home/nhat/projectcuoiky/models/xgb_baseline.joblib")
joblib.dump(lgb_model, "/home/nhat/projectcuoiky/models/lgb_baseline.joblib")
torch.save(mlp_model.state_dict(), "/home/nhat/projectcuoiky/models/
 ↪mlp_pytorch_baseline.pth")
```

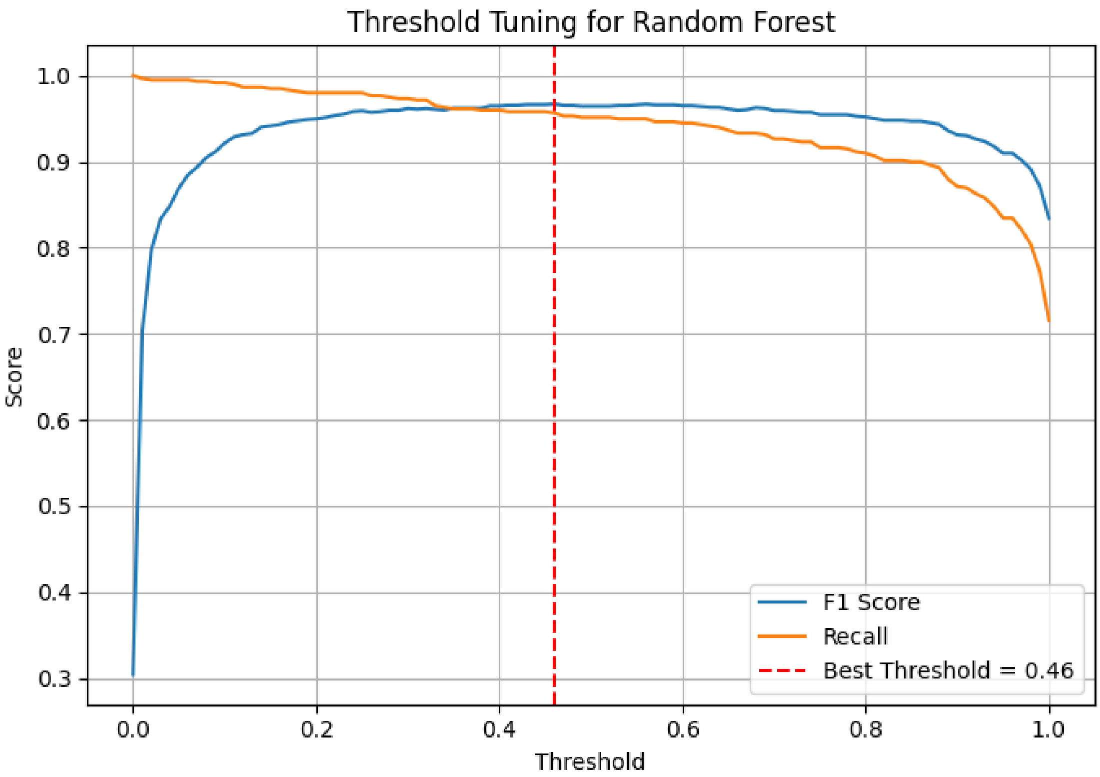
[31]:
```
# === 6. Threshold Tuning for Models ===
# Get predictions on test data
svm_probs = svm_model.predict_proba(X_test_scaled)[:, 1]
rf_probs = rf_model.predict_proba(X_test_df)[:, 1]
xgb_probs = xgb_model.predict_proba(X_test_df)[:, 1]
lgb_probs = lgb_model.predict_proba(X_test_df)[:, 1]
mlp_preds, mlp_probs = get_pytorch_predictions(mlp_model, X_test_scaled)

# Tune thresholds for each model
print("\n=== Tuning SVM Threshold ===")
svm_best_threshold = tune_thresholds(y_test, svm_probs, "SVM")

print("\n=== Tuning Random Forest Threshold ===")
rf_best_threshold = tune_thresholds(y_test, rf_probs, "Random Forest")

print("\n=== Tuning XGBoost Threshold ===")
xgb_best_threshold = tune_thresholds(y_test, xgb_probs, "XGBoost")

print("\n=== Tuning LightGBM Threshold ===")
lgb_best_threshold = tune_thresholds(y_test, lgb_probs, "LightGBM")

print("\n=== Tuning MLP Threshold ===")
mlp_best_threshold = tune_thresholds(y_test, mlp_probs, "MLP")

# Summarize optimal thresholds
print("\n=== Summary of Optimal Thresholds ===")
print(f"SVM: {svm_best_threshold:.2f}")
print(f"Random Forest: {rf_best_threshold:.2f}")
print(f"XGBoost: {xgb_best_threshold:.2f}")
```

```
print(f"LightGBM: {lgb_best_threshold:.2f}")
print(f"MLP: {mlp_best_threshold:.2f}")
```

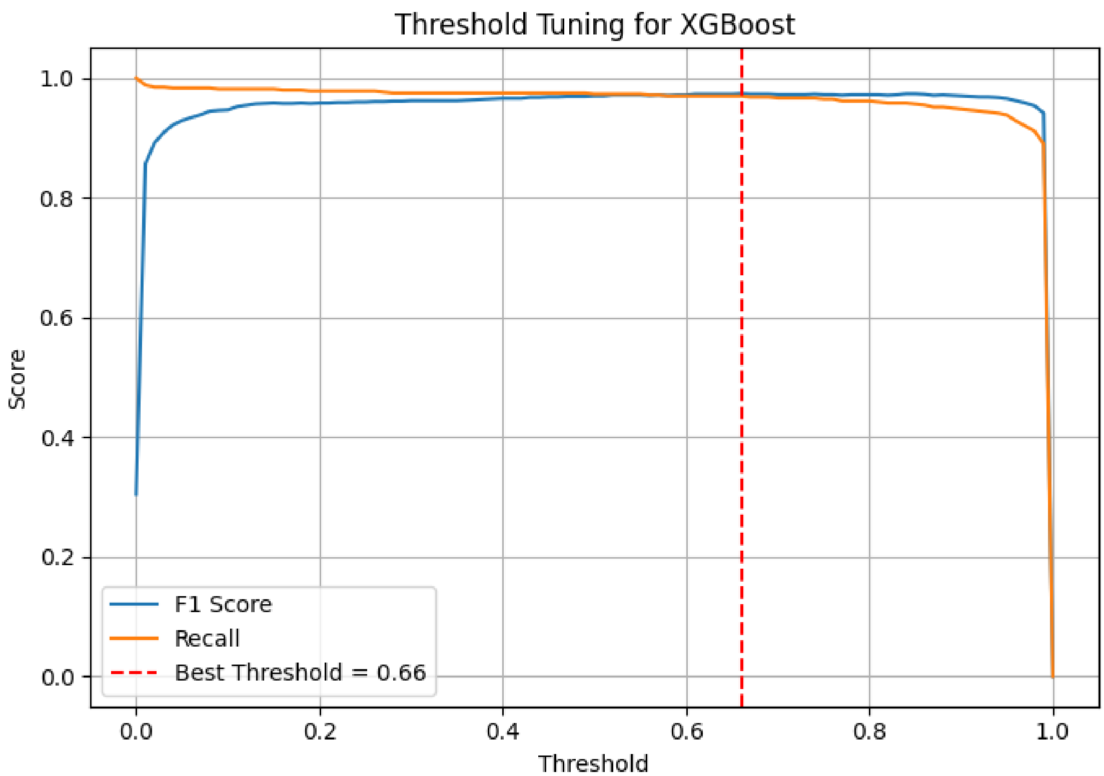
```
=== Tuning SVM Threshold ===
```



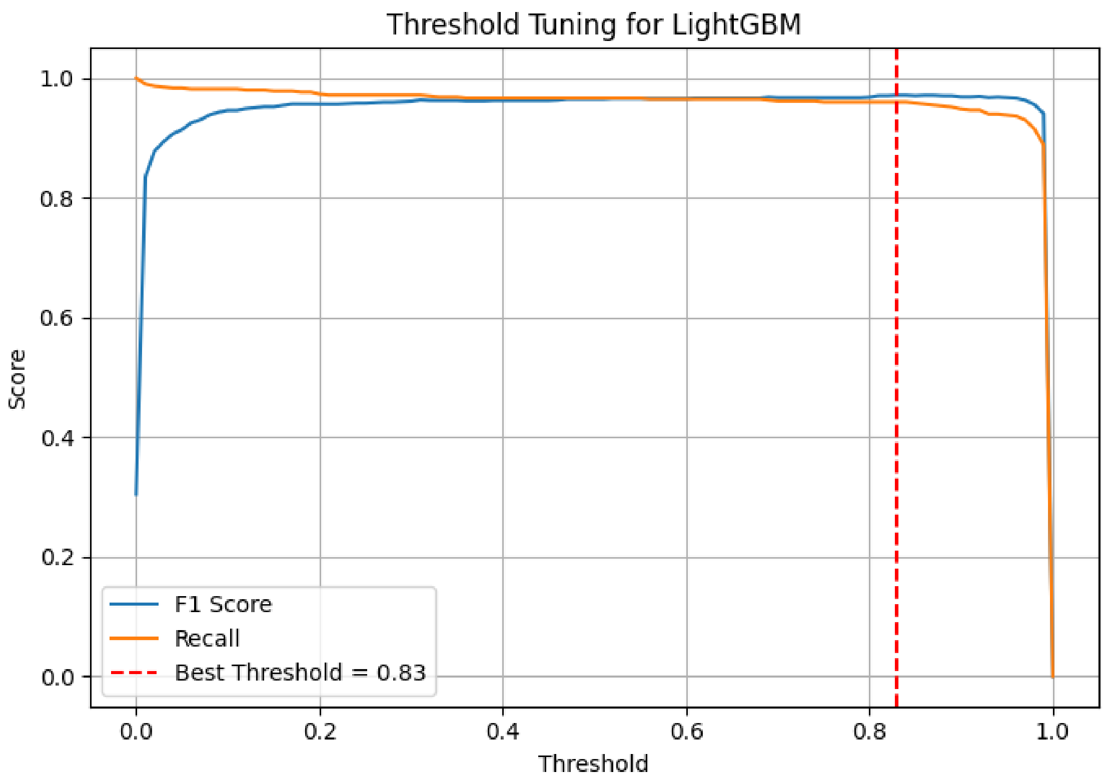

```
Optimal threshold for SVM = 0.59 with F1 = 0.9204 and Recall = 0.8696

=== Tuning Random Forest Threshold ===
```



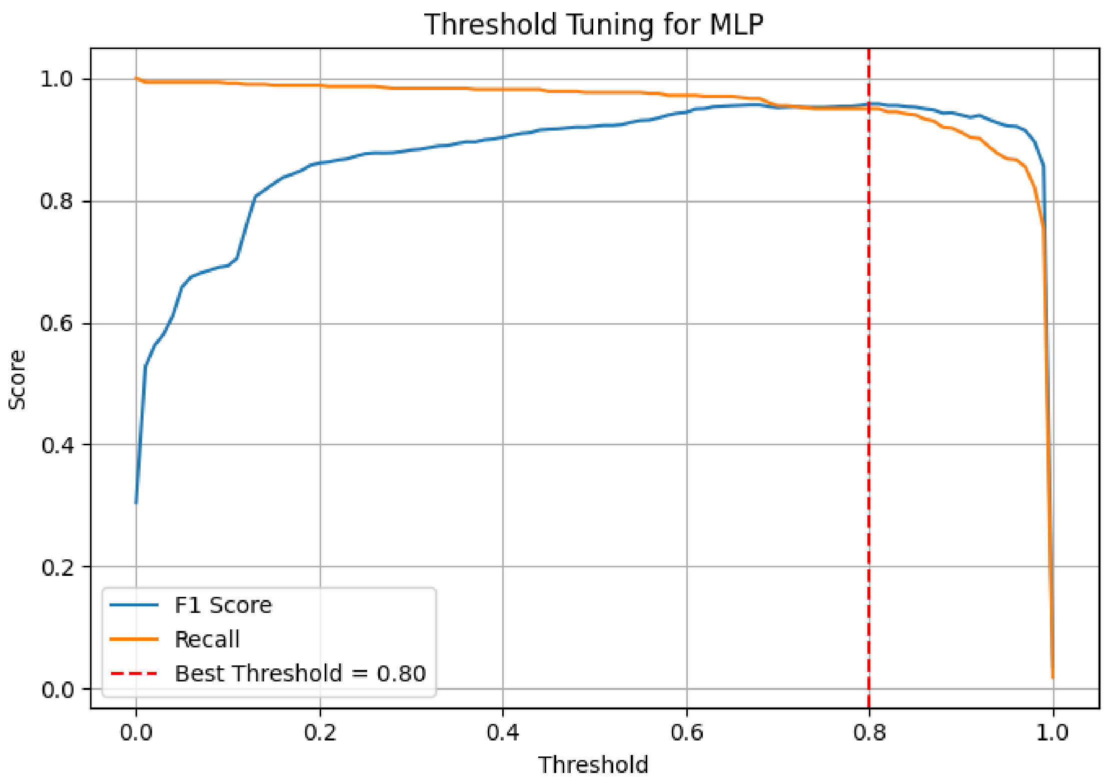

```
Optimal threshold for Random Forest = 0.46 with F1 = 0.9670 and Recall = 0.9565

=== Tuning XGBoost Threshold ===
```




```
Optimal threshold for XGBoost = 0.66 with F1 = 0.9740 and Recall = 0.9699

=== Tuning LightGBM Threshold ===
```




```
Optimal threshold for LightGBM = 0.83 with F1 = 0.9712 and Recall = 0.9599

=== Tuning MLP Threshold ===
```




```
Optimal threshold for MLP = 0.80 with F1 = 0.9578 and Recall = 0.9498

=== Summary of Optimal Thresholds ===
SVM: 0.59
Random Forest: 0.46
XGBoost: 0.66
LightGBM: 0.83
MLP: 0.80
```

[32]:

```
# === 6. Evaluate and Plot ROC Curves ===
from sklearn.metrics import roc_curve
import matplotlib.pyplot as plt


def evaluate_model(model, X_test, y_test, name, is_pytorch=False, threshold=0.
    ↪5):
    if is_pytorch:
        preds, probs = get_pytorch_predictions(model, X_test, threshold)
    else:
        probs = model.predict_proba(X_test)[:, 1]
        preds = (probs > threshold).astype(int)
```

```python
    cm = confusion_matrix(y_test, preds)
    auc_val = roc_auc_score(y_test, probs)
    print(f"\n--- {name} ---")
    print("Confusion Matrix:\n", cm)
    print(f"TP: {cm[1, 1]} | FN: {cm[1, 0]} | FP: {cm[0, 1]} | TN: {cm[0, 0]}")
    print(f"Recall (Malicious): {cm[1, 1] / (cm[1, 1] + cm[1, 0]):.4f}")
    print(f"F1 (Malicious): {f1_score(y_test, preds):.4f}")
    print(f"ROC AUC: {auc_val:.4f}")
    fpr, tpr, _ = roc_curve(y_test, probs)
    plt.plot(fpr, tpr, label=f"{name} (AUC={auc_val:.2f})")

print("\n--- Malware Detection Focused Evaluation ---")
plt.figure(figsize=(8,6))
evaluate_model(svm_model, X_test_scaled, y_test, name="SVM", threshold=0.4)
evaluate_model(rf_model, X_test_df, y_test, name="Random Forest", threshold=0.4)
evaluate_model(xgb_model, X_test_df, y_test, name="XGBoost", threshold=0.4)
evaluate_model(lgb_model, X_test_df, y_test, name="LightGBM", threshold=0.4)
evaluate_model(mlp_model, X_test_scaled, y_test, name="MLP", is_pytorch=True,␣
 ↪threshold=0.4)

plt.plot([0, 1], [0, 1], 'k--')
plt.title("ROC Curves for Malware Detection")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()

# === 7. Save the Optimized Thresholds ===
# Save the threshold values for future inference
thresholds_dict = {
    'svm': svm_best_threshold,
    'random_forest': rf_best_threshold,
    'xgboost': xgb_best_threshold,
    'lightgbm': lgb_best_threshold,
    'mlp': mlp_best_threshold
}

# Save thresholds as a joblib file
joblib.dump(thresholds_dict, "/home/nhat/projectcuoiky/models/
 ↪optimal_thresholds.joblib")
print("Optimal thresholds saved to /home/nhat/projectcuoiky/models/
 ↪optimal_thresholds.joblib")
```

```
--- Malware Detection Focused Evaluation ---
```

```
--- SVM ---
Confusion Matrix:
 [[2707   26]
 [  74  524]]
TP: 524 | FN: 74 | FP: 26 | TN: 2707
Recall (Malicious): 0.8763
F1 (Malicious): 0.9129
ROC AUC: 0.9776

--- Random Forest ---
Confusion Matrix:
 [[2717   16]
 [  25  573]]
TP: 573 | FN: 25 | FP: 16 | TN: 2717
Recall (Malicious): 0.9582
F1 (Malicious): 0.9655
ROC AUC: 0.9970

--- XGBoost ---
Confusion Matrix:
 [[2707   26]
 [  15  583]]
TP: 583 | FN: 15 | FP: 26 | TN: 2707
Recall (Malicious): 0.9749
F1 (Malicious): 0.9660
ROC AUC: 0.9981

--- LightGBM ---
Confusion Matrix:
 [[2708   25]
 [  20  578]]
TP: 578 | FN: 20 | FP: 25 | TN: 2708
Recall (Malicious): 0.9666
F1 (Malicious): 0.9625
ROC AUC: 0.9979

--- MLP ---
Confusion Matrix:
 [[2618  115]
 [  11  587]]
TP: 587 | FN: 11 | FP: 115 | TN: 2618
Recall (Malicious): 0.9816
F1 (Malicious): 0.9031
ROC AUC: 0.9923

--- SVM ---
Confusion Matrix:
```

```
 [[2707   26]
 [  74  524]]
TP: 524 | FN: 74 | FP: 26 | TN: 2707
Recall (Malicious): 0.8763
F1 (Malicious): 0.9129
ROC AUC: 0.9776

--- Random Forest ---
Confusion Matrix:
 [[2717   16]
 [  25  573]]
TP: 573 | FN: 25 | FP: 16 | TN: 2717
Recall (Malicious): 0.9582
F1 (Malicious): 0.9655
ROC AUC: 0.9970

--- XGBoost ---
Confusion Matrix:
 [[2707   26]
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TP: 583 | FN: 15 | FP: 26 | TN: 2707
Recall (Malicious): 0.9749
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--- LightGBM ---
Confusion Matrix:
 [[2708   25]
 [  20  578]]
TP: 578 | FN: 20 | FP: 25 | TN: 2708
Recall (Malicious): 0.9666
F1 (Malicious): 0.9625
ROC AUC: 0.9979

--- MLP ---
Confusion Matrix:
 [[2618  115]
 [  11  587]]
TP: 587 | FN: 11 | FP: 115 | TN: 2618
Recall (Malicious): 0.9816
F1 (Malicious): 0.9031
ROC AUC: 0.9923
```

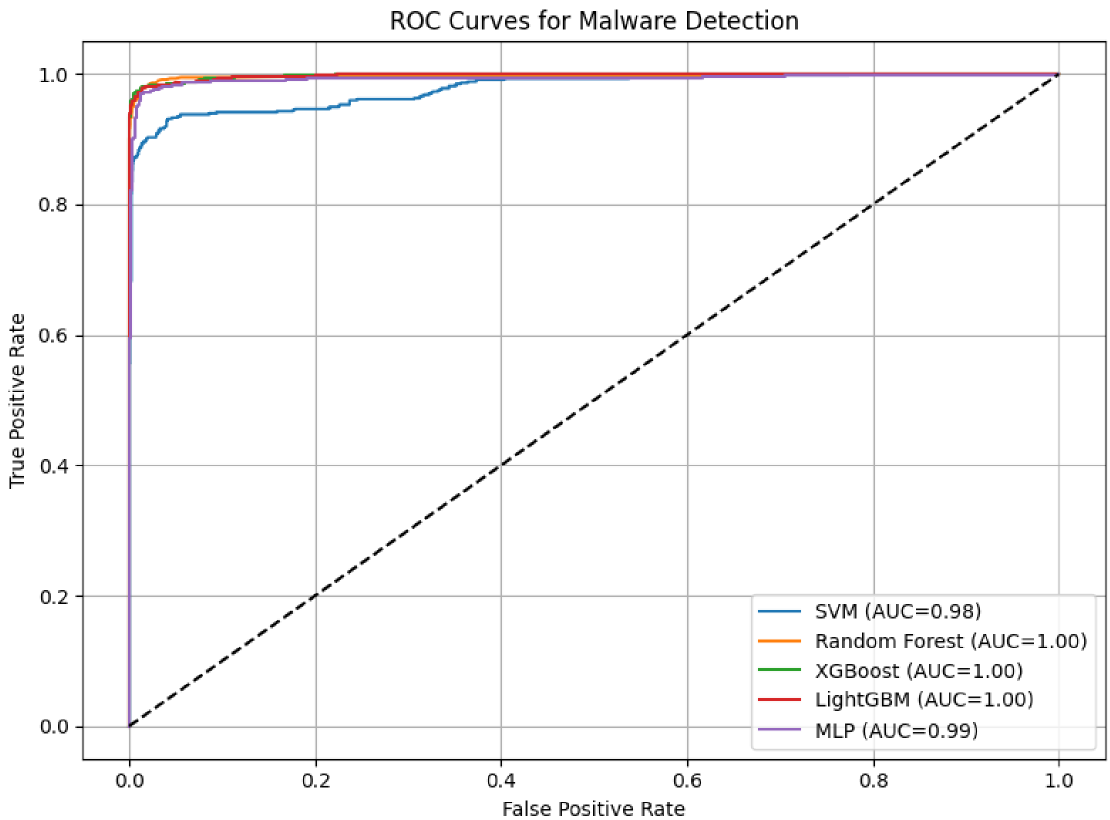


```
Optimal thresholds saved to
/home/nhat/projectcuoiky/models/optimal_thresholds.joblib
```

[33]:

```python
# === 7. Evaluate and Plot ROC Curves ===
from sklearn.metrics import roc_curve

def evaluate_model(model, X_test, y_test, name, is_pytorch=False, threshold=0.
 ↪5):
    if is_pytorch:
        preds, probs = get_pytorch_predictions(model, X_test, threshold)
    else:
        probs = model.predict_proba(X_test)[:, 1]
        preds = (probs > threshold).astype(int)

    cm = confusion_matrix(y_test, preds)
    auc_val = roc_auc_score(y_test, probs)
    print(f"\n--- {name} ---")
    print("Confusion Matrix:\n", cm)
    print(f"TP: {cm[1, 1]} | FN: {cm[1, 0]} | FP: {cm[0, 1]} | TN: {cm[0, 0]}")
    print(f"Recall (Malicious): {cm[1, 1] / (cm[1, 1] + cm[1, 0]):.4f}")
    print(f"F1 (Malicious): {f1_score(y_test, preds):.4f}")
```

```
    print(f"ROC AUC: {auc_val:.4f}")
    fpr, tpr, _ = roc_curve(y_test, probs)
    plt.plot(fpr, tpr, label=f"{name} (AUC={auc_val:.2f})")

print("\n--- Malware Detection Focused Evaluation ---")
plt.figure(figsize=(8,6))
evaluate_model(svm_model, X_test_scaled, y_test, name="SVM",␣
 ↪threshold=svm_best_threshold)
evaluate_model(rf_model, X_test_df, y_test, name="Random Forest",␣
 ↪threshold=rf_best_threshold)
evaluate_model(xgb_model, X_test_df, y_test, name="XGBoost",␣
 ↪threshold=xgb_best_threshold)
evaluate_model(lgb_model, X_test_df, y_test, name="LightGBM",␣
 ↪threshold=lgb_best_threshold)
evaluate_model(mlp_model, X_test_scaled, y_test, name="MLP", is_pytorch=True,␣
 ↪threshold=mlp_best_threshold)

plt.plot([0, 1], [0, 1], 'k--')
plt.title("ROC Curves for Malware Detection")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
--- Malware Detection Focused Evaluation ---

--- SVM ---
Confusion Matrix:
 [[2721   12]
 [  78  520]]
TP: 520 | FN: 78 | FP: 12 | TN: 2721
Recall (Malicious): 0.8696
F1 (Malicious): 0.9204
ROC AUC: 0.9776

--- Random Forest ---
Confusion Matrix:
 [[2720   13]
 [  27  571]]
TP: 571 | FN: 27 | FP: 13 | TN: 2720
Recall (Malicious): 0.9548
F1 (Malicious): 0.9662
ROC AUC: 0.9970
```

```
--- XGBoost ---
Confusion Matrix:
 [[2720   13]
 [  18  580]]
TP: 580 | FN: 18 | FP: 13 | TN: 2720
Recall (Malicious): 0.9699
F1 (Malicious): 0.9740
ROC AUC: 0.9981

--- LightGBM ---
Confusion Matrix:
 [[2723   10]
 [  24  574]]
TP: 574 | FN: 24 | FP: 10 | TN: 2723
Recall (Malicious): 0.9599
F1 (Malicious): 0.9712
ROC AUC: 0.9979

--- MLP ---
Confusion Matrix:
 [[2713   20]
 [  30  568]]
TP: 568 | FN: 30 | FP: 20 | TN: 2713
Recall (Malicious): 0.9498
F1 (Malicious): 0.9578
ROC AUC: 0.9923

--- SVM ---
Confusion Matrix:
 [[2721   12]
 [  78  520]]
TP: 520 | FN: 78 | FP: 12 | TN: 2721
Recall (Malicious): 0.8696
F1 (Malicious): 0.9204
ROC AUC: 0.9776

--- Random Forest ---
Confusion Matrix:
 [[2720   13]
 [  27  571]]
TP: 571 | FN: 27 | FP: 13 | TN: 2720
Recall (Malicious): 0.9548
F1 (Malicious): 0.9662
ROC AUC: 0.9970

--- XGBoost ---
Confusion Matrix:
 [[2720   13]
```

```
 [  18  580]]
TP: 580 | FN: 18 | FP: 13 | TN: 2720
Recall (Malicious): 0.9699
F1 (Malicious): 0.9740
ROC AUC: 0.9981

--- LightGBM ---
Confusion Matrix:
 [[2723   10]
 [  24  574]]
TP: 574 | FN: 24 | FP: 10 | TN: 2723
Recall (Malicious): 0.9599
F1 (Malicious): 0.9712
ROC AUC: 0.9979

--- MLP ---
Confusion Matrix:
 [[2713   20]
 [  30  568]]
TP: 568 | FN: 30 | FP: 20 | TN: 2713
Recall (Malicious): 0.9498
F1 (Malicious): 0.9578
ROC AUC: 0.9923
```