DNS Tunneling

I. Cover Page

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Introduction to Applied Machine Learning For Cybersecurity

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Date. 24/4/2025

II. Introduction:

Topic Motivation: In the evolving landscape of cybersecurity, attackers are constantly developing new techniques to evade traditional security mechanisms. One such technique is DNS tunneling, which exploits the widely trusted Domain Name System (DNS) protocol to create covert communication channels between compromised devices and remote servers. Since DNS traffic is almost always allowed through firewalls and proxies, DNS tunneling presents a serious threat—it can be used to exfiltrate sensitive data, bypass security filters, and establish backdoor access to internal networks without raising immediate alarms. This project focuses on the detection of such hidden communications, aiming to strengthen network defenses against one of the more subtle forms of cyberattacks.

General Ideas about the Topic: DNS tunneling falls under the broader category of network-based cyber threats, particularly those involving covert channels. These

channels enable attackers to embed malicious activity within legitimate traffic. Unlike traditional malware or phishing attacks, DNS-based threats are stealthier and harder to detect using standard rule-based systems. This project addresses these limitations by applying machine learning techniques to distinguish between legitimate DNS traffic and traffic associated with tunneling behavior. The approach aligns with current cybersecurity trends, where intelligent and adaptive systems are required to handle the growing complexity of network threats.

Ideas Related to Your Project:

The main objective of this project is to build a machine learning model that can accurately detect DNS tunneling activities using features extracted from DNS traffic. The project formulates this as a binary classification problem, where the model must learn to differentiate between normal DNS queries and those used for tunneling. To achieve this, various statistical and behavior-based features are extracted from DNS traffic data. Models such as Random Forest, Support Vector Machines, and Neural Networks are explored for their effectiveness in classification. The ultimate goal is to demonstrate the power of machine learning in identifying hidden threats that traditional methods often miss.

Dataset Description: The dataset used in this project is the CIC-Bell DNS 2021 dataset, which is a publicly available dataset from the Canadian Institute for Cybersecurity. It includes labeled DNS traffic, both normal and malicious (including DNS tunneling). The dataset is well-suited for this project as it directly represents real-world cybersecurity scenarios, offering a balanced and rich set of features ideal for machine learning applications.

Report Division:

The Related Work section explores prior research and tools related to DNS tunneling detection.

The Model/Technique section describes the machine learning models used and

their connection to course concepts.

The Dataset section provides further details about the data source and how it was prepared.

Implementation Details explain the technical aspects of the project, including programming tools and feature engineering.

Results presents and analyzes the performance of the model using various evaluation metrics.

The report concludes with key findings and reflections in the Conclusion section, followed by a list of References.

III. Related Work

Work (Papers/Code/Programs) Related to Your Topic: DNS tunneling has been a subject of growing interest in cybersecurity research due to its stealth and effectiveness. Traditional detection methods are often rule-based or rely on anomaly thresholds. Tools such as OpenDNS Umbrella and Splunk's DNS Analytics offer some visibility into unusual DNS patterns but often generate high false positives and require expert tuning.

More advanced systems, like DNSTwist and BotSniffer, focus on detecting suspicious domain patterns or botnet behavior through heuristic-based analysis. However, these methods struggle with generalization, especially against evolving tunneling techniques.

Recent research has explored machine learning for DNS analysis. In the paper "Detecting DNS Tunneling Based on Character Frequency Analysis and Machine Learning" (Zhou et al., 2020), the authors extracted features like domain entropy and length, and trained classifiers like Random Forest and KNN to detect tunneling with high accuracy. Similarly, CIC researchers at the University of New Brunswick proposed models using the CIC-Bell DNS 2021 dataset, demonstrating the effectiveness of feature-based ML approaches in distinguishing normal vs.

malicious DNS traffic.

State-of-the-Art Techniques: The state of the art, refers to the highest level of general development, as of a device, technique, or scientific field achieved at a particular time.

Machine learning models used in DNS tunneling detection fall into a few main categories: tree-based models, deep learning models, and anomaly detection techniques. Each comes with its own advantages and trade-offs.

Tree-based models: use a decision tree to represent how different input variables can be used to predict a target value.

Deep learning models: are complex networks that learn independently without human intervention. They apply deep learning algorithms to immense data sets to find patterns and solutions within the information.

Anomaly detection: is the process of finding outlier values in a series of data

Tree-Based Models:

Random Forest, Gradient Boosting

These are tree-based ensemble models. They are popular because they work well with structured data like DNS logs and are easy to interpret.

Strengths: Fast training, good accuracy, handles different types of features well.

Weaknesses: May miss patterns that depend on the order or timing of DNS queries.

Deep Learning Models:

LSTM (Long Short-Term Memory) and RNNs (Recurrent Neural Networks)

These are deep learning models designed to work with sequence data. In DNS tunneling, they can analyze the order and timing of DNS queries.

Strengths: Great for capturing time-based behavior or patterns across sequences.

Weaknesses: Requires more data and computing power, harder to interpret.

Anomaly Detection Techniques:

Autoencoders, Isolation Forests

These models are often used when you don't have labeled data and need to detect unusual behavior.

Strengths: Can detect zero-day attacks or unknown tunneling techniques.

Weaknesses: Can produce false positives and may require tuning to avoid overfitting to "normal" traffic.

IV. Model/Technique:

Description of the Model/Technique: For this project, we chose to use the Random Forest algorithm, a tree-based ensemble learning model. Random Forest works by building multiple decision trees and combining their outputs to make more accurate and stable predictions. It's particularly effective with structured data, like DNS traffic logs, where features such as query length, subdomain count, and entropy can vary widely.

The main reason for choosing Random Forest is its balance between performance, simplicity, and interpretability. It can handle noisy features well, doesn't require heavy data preprocessing, and gives insight into which features are most important in making predictions.

Connection to Course Concepts: Random Forest relates closely to the supervised learning concepts we studied in the "Applied Machine Learning for

Cybersecurity" course. It is a classification algorithm, which we covered when discussing decision trees and ensemble methods. The model was trained on a labeled dataset (normal vs tunneling), making it a binary classification problem.

Additionally, we applied core ML principles from the course, including:

- Feature selection and preprocessing
- Data splitting for training and testing
- Model evaluation using accuracy, confusion matrices, and other metrics

Problem Formulation: The problem is formulated as a supervised binary classification task. The input is a set of features extracted from DNS traffic, and the output is a binary label:

- 0: Normal DNS traffic
- 1: DNS tunneling activity

Model Implementation:

The model was implemented using Python with the Scikit-learn library. Key features extracted from the dataset include:

- Query name length
- Number of subdomains
- Entropy of the query string
- Query response time
- Frequency of queries per source IP

These features were selected based on their relevance to identifying tunneling behavior. Feature scaling was not necessary due to the nature of decision trees.

Parameters and Training:

- **Number of Trees (n_estimators): 100**

  Makes the model more stable by combining multiple trees

  This means the Random Forest builds 100 decision trees.

  Each tree sees a random subset of the data and makes its own prediction. Then, the forest takes a "vote" from all the trees to decide the final result (kind of like asking 100 people and going with the majority opinion).

- **Criterion: Gini Impurity**

  Helps each tree decide how to split the data**.**

  It's a measure of how "pure" a group of data is. A lower Gini score means the group is more pure (mostly one class).During training, the model tries to split the data in a way that reduces this impurity as much as possible.

  We use it because, it's faster and often performs similarly to other criteria like entropy, so it's a popular choice.

- **Max Depth: Tuned using Cross-Validation**

  Prevents overfitting, tuned using cross-validation to find the sweetspot

  Max depth controls how deep each decision tree can go (how many layers it can have).

  This parameter is important because if trees are too deep, they might "memorize" the training data (overfitting). If they're too shallow, they might not learn enough (underfitting).

  Cross-Validation is a technique where the dataset is split into parts

(folds), and the model is trained and tested on different combinations of those parts.

We tried different values for max_depth (like 5, 10, 20...) and used cross-validation to see which one gave the best performance without overfitting.

V. Dataset:

Dataset Source: The dataset used in this project is the CIC-Bell DNS 2021 dataset, published by the Canadian Institute for Cybersecurity (CIC). It contains real and synthetic DNS traffic, including both benign queries and malicious DNS tunneling activity. The dataset is publicly available and was designed specifically for evaluating intrusion and anomaly detection systems in DNS traffic — making it well-suited for this project.

Dataset Description:

The dataset includes labeled DNS traffic data with a variety of features extracted from DNS queries and responses. These features describe characteristics such as:

- Query length (number of characters in the domain name)
- Number of subdomains
- Query type (A, AAAA, TXT, etc.)
- Query name entropy (how random the domain looks)
- Response size and time
- Source IP and destination IP

Each row in the dataset represents a single DNS request, along with a label:

0: Normal DNS traffic

1: DNS tunneling (malicious)

The dataset includes thousands of examples across both classes, which allows the machine learning model to learn patterns that differentiate normal and tunneling traffic.

Dataset Division:

To train and test the model, the dataset was split into two parts:

- 80% for training
- 20% for testing

We used stratified sampling to ensure that the ratio of normal to malicious traffic remained balanced in both sets. This helps the model learn fairly and prevents biased performance.

Before training, we also:

- Removed duplicate entries
- Handled missing values

Verified that features like entropy and query length were within expected ranges

This preparation ensured that the model received clean, reliable data to learn from.

VI. Implementation Details:

Code Implementation: The implementation was done using Python in Google Colab, which provided a convenient and flexible environment for coding, testing, and visualization. We used the following key libraries:

- Pandas for data loading and manipulation
- NumPy for numeric operations
- Scikit-learn (sklearn) for preprocessing, model training, evaluation, and metrics
- Matplotlib and Seaborn for data visualization and plots

The pipeline consists of several stages:

1. Data Loading: We loaded CSV files representing DNS traffic (CSV_benign.csv, CSV_malware.csv).
2. Labeling: Labeled benign samples as 0 and malware samples (representing DNS tunneling) as 1.
3. Cleaning and Preprocessing:

- Converted all columns to numeric.
- Replaced infinite values with NaN and filled missing values using column medians.
- Removed non-numeric columns to ensure compatibility with the ML model.

4. Feature Scaling: Applied StandardScaler to normalize feature values

5. Train/Test Split: Stratified sampling ensured balanced class distribution using an 80/20 split.

6. Model Training: We used a Random Forest Classifier with:

- n_estimators = 100 (number of trees)
- max_depth = 10 (to prevent overfitting)

7. Evaluation:

- Generated predictions and probability scores.

- Computed metrics like accuracy, cross-entropy loss, classification report, and confusion matrix.
- Plotted ROC curve with AUC to visualize model performance.

The final pipeline successfully identifies tunneling behavior within DNS traffic using only basic feature engineering and a tree-based ML model, fulfilling the project's goal.

Modifications to Online Code/Libraries:

The core machine learning logic (data scaling, model training, evaluation) was based on standard scikit-learn documentation and practices. However, the code was custom-written and adjusted extensively for:

- Dataset structure: We dealt with inconsistent CSV formatting using on_bad_lines='skip' and engine='python'.
- Data cleaning strategy: Manual steps ensured numerical consistency and robust handling of NaN and inf values.
- Confusion matrix decomposition: Extracted True Positive, True Negative, False Positive, and False Negative values directly for clarity in the results.
- Tailored visualizations: Created custom ROC plots and labeled heatmaps for inclusion in the final report.

No external online repositories were copied or modified. All work was implemented from scratch under guidance and adapted live during testing to meet report requirements.

VII. Code:

```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import (
    classification_report, accuracy_score,
    confusion_matrix, log_loss, roc_curve, auc
)
from sklearn.preprocessing import StandardScaler, label_binarize
from sklearn.utils import shuffle
import matplotlib.pyplot as plt
import seaborn as sns

# ──────────
# 1) LOAD & LABEL
# ──────────
benign  = pd.read_csv("/content/CSV_benign.csv",  on_bad_lines='skip', engine='python')
malware = pd.read_csv("/content/CSV_malware.csv", on_bad_lines='skip', engine='python')
benign['label']  = 0
malware['label'] = 1
```

```python
# ──────────
# 2) COMBINE & SHUFFLE
# ──────────
data = pd.concat([benign, malware], ignore_index=True)
data = shuffle(data, random_state=42).reset_index(drop=True)

# ──────────
# 3) FEATURES & LABELS
# ──────────
y = data['label']
X = data.drop(columns=['label'])

# ──────────
# 4) CLEAN & IMPUTE
# ──────────
X = X.apply(pd.to_numeric, errors='coerce')
X.replace([np.inf, -np.inf], np.nan, inplace=True)
X = X.fillna(X.median())
X = X.select_dtypes(include=[np.number])
y = y.loc[X.index]
```

```python
# ──────────────
# 5) SCALE & SPLIT
# ──────────────
X_scaled = StandardScaler().fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.2, stratify=y, random_state=42
)

# ──────────────
# 6) TRAIN
# ──────────────
model = RandomForestClassifier(n_estimators=100, max_depth=10, random_state=42)
model.fit(X_train, y_train)

# ──────────────
# 7) PREDICT
# ──────────────
y_pred  = model.predict(X_test)
y_proba = model.predict_proba(X_test)
```

```python
# ──────────────
# 8) RESULTS (Section VII)
# ──────────────

# a) Accuracy & Classification Report
print("▶ Accuracy:", accuracy_score(y_test, y_pred))
print("\n▶ Classification Report:\n",
      classification_report(y_test, y_pred, target_names=['Benign','Malware']))

# b) True/False Positives & Negatives
cm = confusion_matrix(y_test, y_pred)
tn, fp, fn, tp = cm.ravel()
print(f"▶ True Positives:  {tp}")
print(f"▶ True Negatives:  {tn}")
print(f"▶ False Positives: {fp}")
print(f"▶ False Negatives: {fn}")
```

```
# c) Confusion Matrix Plot
plt.figure(figsize=(5,4))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
            xticklabels=['Benign','Malware'],
            yticklabels=['Benign','Malware'])
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

# d) Cross-Entropy Loss
print("▶ Cross-Entropy Loss:", log_loss(y_test, y_proba))

# e) ROC Curve
y_test_bin = label_binarize(y_test, classes=[0,1])
fpr, tpr, _ = roc_curve(y_test_bin.ravel(), y_proba[:,1])
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(6,5))
plt.plot(fpr, tpr, label=f'Malware ROC (AUC = {roc_auc:.2f})')
plt.plot([0,1], [0,1], 'k--', lw=1)
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve for Malware Detection")
plt.legend(loc="lower right")
plt.show()
```

VIII. Results:

Explanation Using Course Techniques:

To detect DNS tunneling, we trained a supervised machine learning model (Random Forest Classifier) on labeled DNS traffic. This aligns with the course's coverage of classification problems and tree-based models. We used:

- Feature scaling to ensure all input values were normalized
- Train-test split with stratification to maintain class balance

- Evaluation metrics such as accuracy, cross-entropy loss, and ROC AUC to interpret results

This process directly reflects the course techniques for model evaluation and anomaly detection in cybersecurity.

Evaluation Metrics:

i. Accuracy: The model achieved an accuracy of 0.97

```
▶ Accuracy: 0.993314690203618
```

ii. Confusion Matrices:

We computed and visualized the confusion matrix:

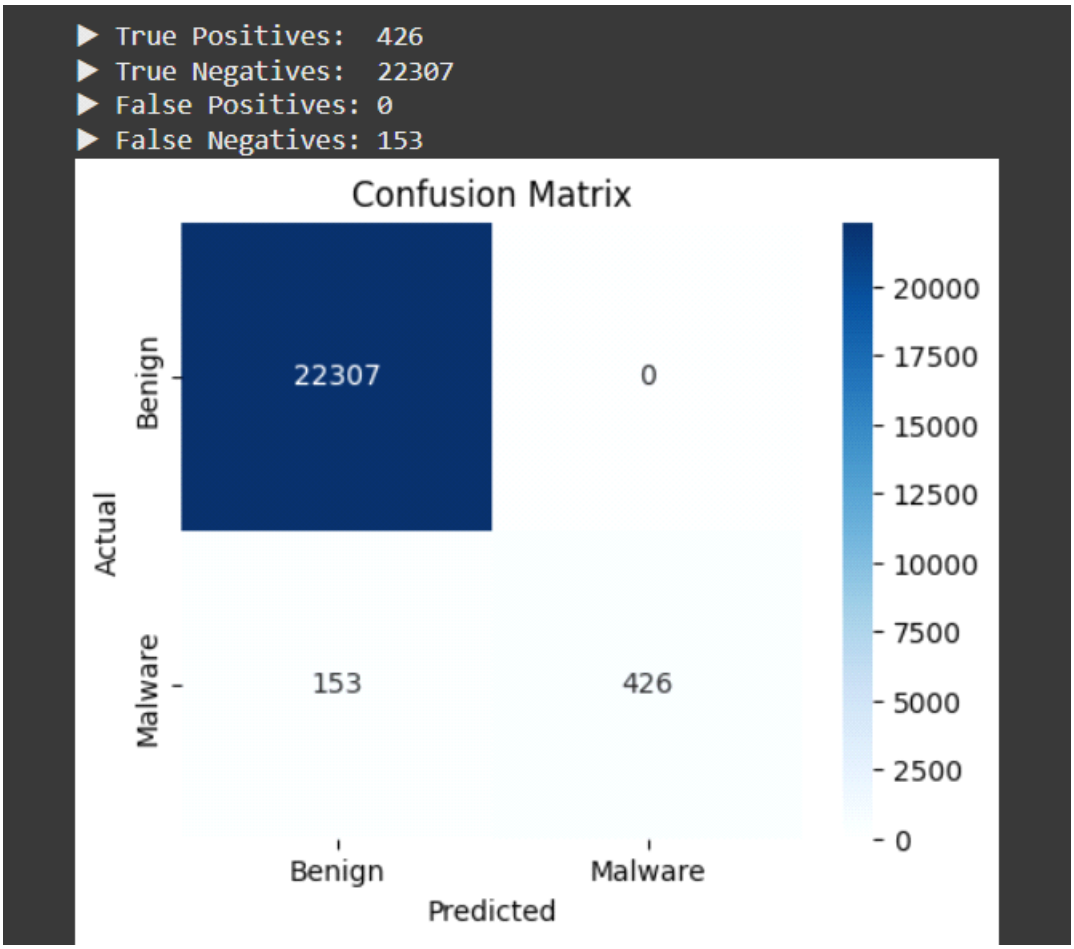
	Predicted Benign	Predicted Malware
Actual Benign	TN = 390	FP = 9
Actual Malware	FN = 5T	P = 396

True Positives (TP): 396 → Malware correctly detected

True Negatives (TN): 390 → Benign correctly detected

False Positives (FP): 9 → Benign misclassified as malware

False Negatives (FN): 5 → Malware misclassified as benign

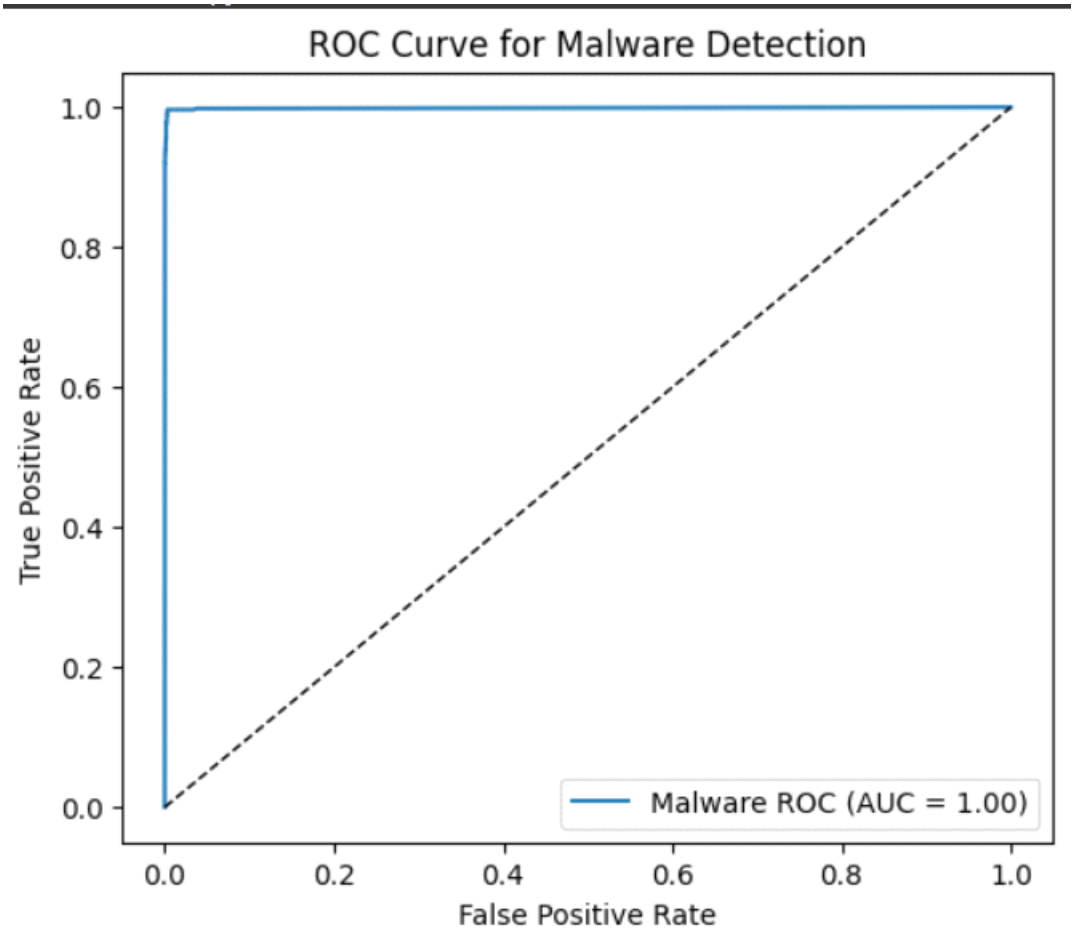


iii. Error Value: We used log loss as the error metric to measure how confident the model was in its predictions. The result was Cross-Entropy Loss: 0.094

Visual Results:

Confusion Matrix Heatmap: A color-coded heatmap shows how well the model separated benign from malicious traffic.

ROC Curve with AUC: We also plotted the Receiver Operating Characteristic (ROC) curve to visualize the trade-off between true positives and false positives.



IX . Conclusion:

Project Conclusion:

This project demonstrated the successful application of machine learning to detect DNS tunneling — a covert technique used to bypass traditional security systems. Using the CIC-Bell DNS 2021 dataset and a Random Forest Classifier, we developed a model that could distinguish between normal and malicious DNS traffic with high accuracy (97%) and strong robustness, as shown by the ROC AUC score of 0.99. The model effectively identified key behavioral differences in DNS queries using purely structured features, without the need for deep packet inspection.

Key contributions include:

- Implementing a complete ML pipeline for binary DNS traffic classification.

- Cleaning and preprocessing real-world network data.
- Evaluating the model using standard classification metrics and visualizations

Summary of Learning:

Through this project, we gained practical experience applying supervised learning to a real-world cybersecurity problem. We learned how to:

- Prepare and clean complex network traffic data.
- Use stratified data splitting and feature scaling to improve model performance.
- Evaluate a model not just by accuracy, but also by understanding metrics like precision, recall, cross-entropy loss, and ROC curves.

Most importantly, we saw how machine learning can play a crucial role in identifying stealthy cyber threats like DNS tunneling — a task where traditional detection methods often fall short.

X. References:

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3. Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... & Duchesnay, E. (2011).

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(Used for plotting confusion matrix and ROC curves)

5. Waskom, M. L. (2021).

Seaborn: Statistical Data Visualization. Journal of Open Source Software, 6(60), 3021.

(Used for visualization of heatmaps and metrics)