Network Intrusion Detection on NSL-KDD Dataset

Subtitle: Leveraging Feature Selection & Machine Learning for Enhanced Network Security

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Introduction

Context:

- Modern networks face constant threats from cyber-attacks: DoS, probing, unauthorized access (R2L), and user-to-root (U2R).

Challenge:

- Traditional security measures struggle with novel attack patterns and subtle anomalies.

Goal:

- Use machine learning techniques (feature selection + classification) to detect intrusions in network traffic, improving Intrusion Detection Systems (IDS).

The NSL-KDD Dataset

What is NSL-KDD?

- Benchmark dataset derived from KDD Cup 1999.
- Diverse network connections labeled as normal or various attack types.

Why NSL-KDD?

- Removes redundant records for better evaluation.
- Includes attacks like DoS, Probe, R2L, U2R.

Attack Categories:

- **DoS:** Flooding a network resource (e.g., SYN flood).
- **Probe:** Scanning to find vulnerabilities.
- **R2L:** Unauthorized remote access.
- **U2R:** Gaining root privileges.

Preprocessing Network Data:

Categorical to Numerical:

- One-Hot Encoding for protocol (TCP, UDP, ICMP) and service types.

Aligning Train & Test Sets:

- Ensure identical feature sets.

Label Mapping:

- Map complex attack names to numeric codes (e.g., 0=Normal, 1=DoS).

Scaling Features:

- Standardize feature values to improve model learning.

Feature Selection for Network Intrusion Detection

Why Feature Selection?

- Reduces data volume, speeds up detection, and lowers resource usage.

Methods Used:

- **Univariate Selection (ANOVA F-test):** Top 10% of features.
- **Recursive Feature Elimination (RFE):** Focus on 13 key features.

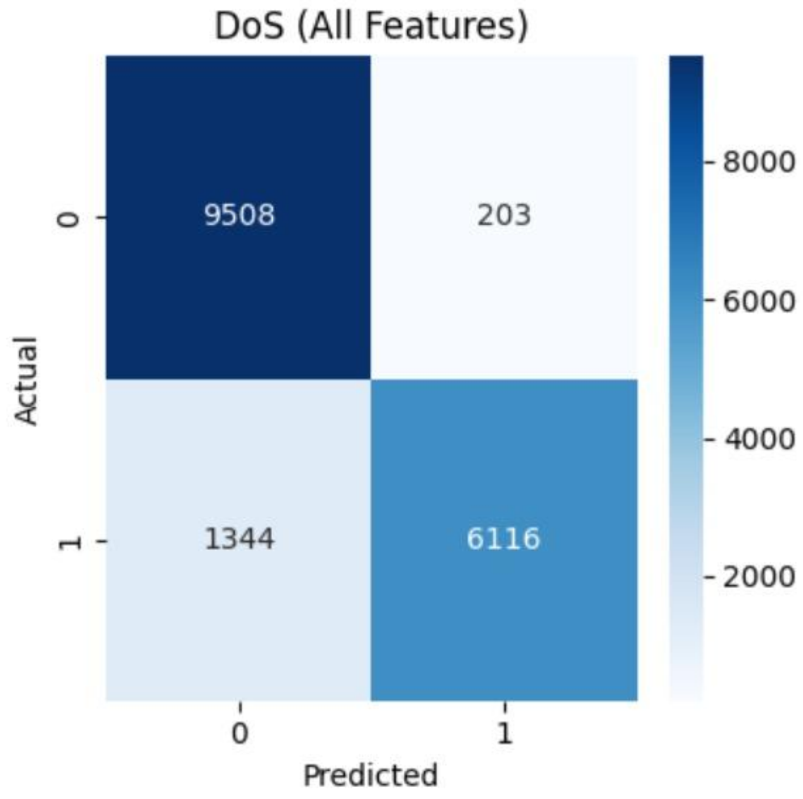
Key Features Identified:

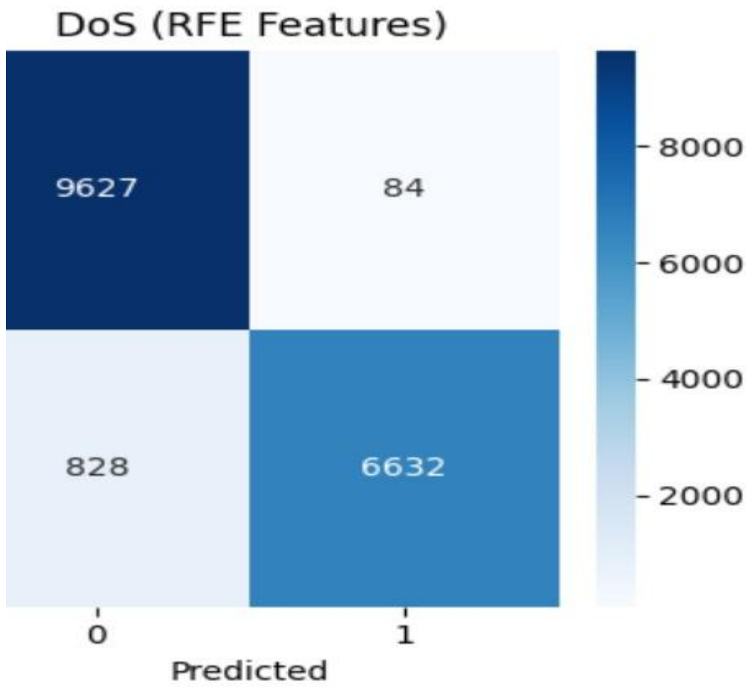
- Examples: same_srv_rate, service_ecr_i.

Evaluation Metrics in a Network Context

Metrics Used:

- **Confusion Matrix:** True positives vs. false negatives.
- **Precision:** Accuracy of raised alerts.
- **Recall:** Proportion of attacks detected.
- **F1-Score:** Balance of precision and recall.
- **ROC & AUC:** Model's ability to distinguish traffic types.


DoS (All Features)
Actual
0
1
9508
203
1344
6116
Predicted
8000
6000
4000
2000


DoS (RFE Features)
9627
84
828
6632
0
1
Predicted
8000
6000
4000
2000

Visualizations & Results

Confusion Matrices:

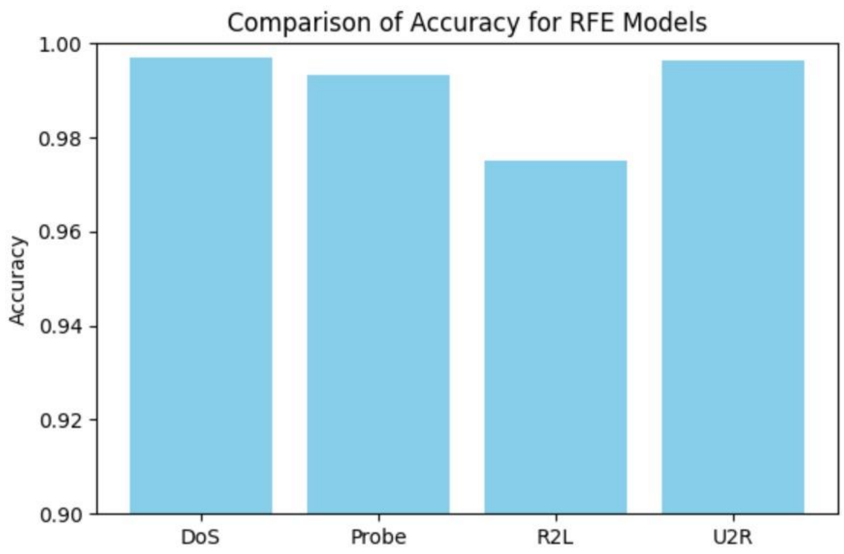
- RFE features yield fewer false alarms.

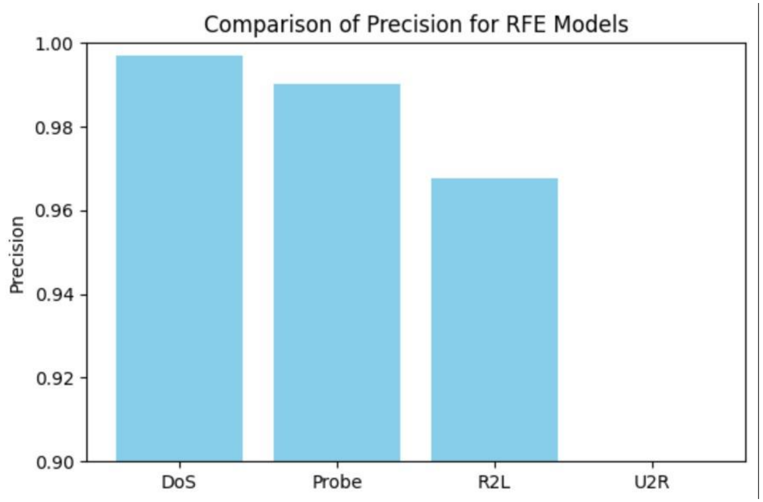
Performance Metrics:

- **DoS:** High accuracy and F1.
- **Probe:** Strong detection.
- **R2L & U2R:** Challenges in subtle attack detection.

ROC Curves:

- High AUC for DoS detection.


Comparison of Accuracy for RFE Models
Accuracy
1.00
0.98
0.96
0.94
0.92
0.90
DoS
Probe
R2L
U2R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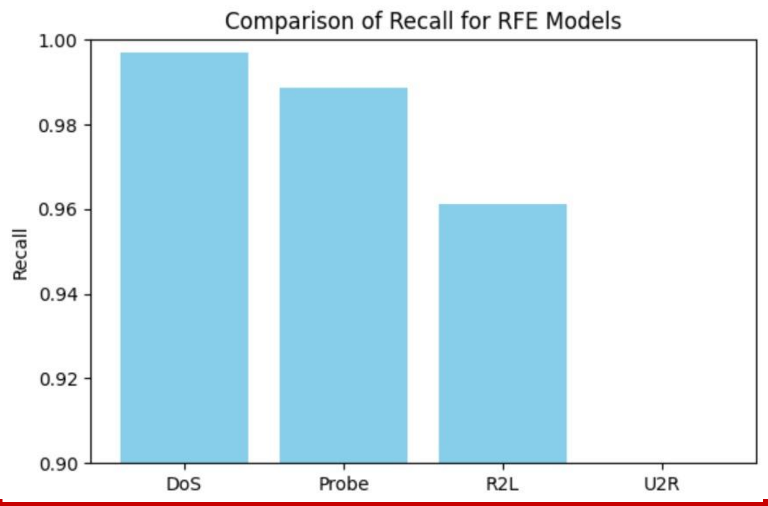
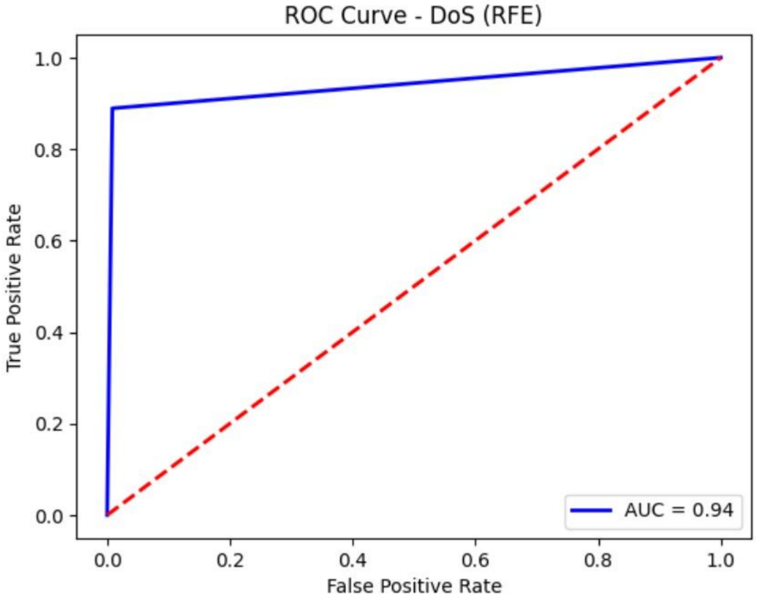
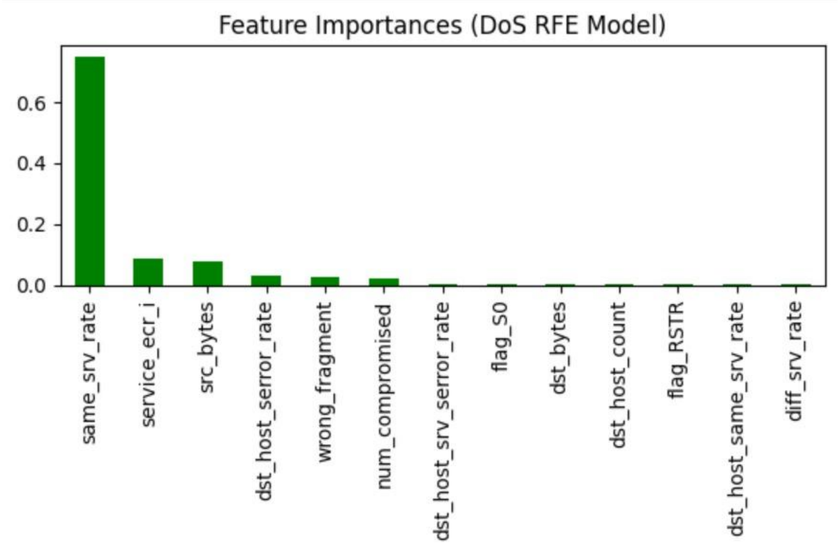
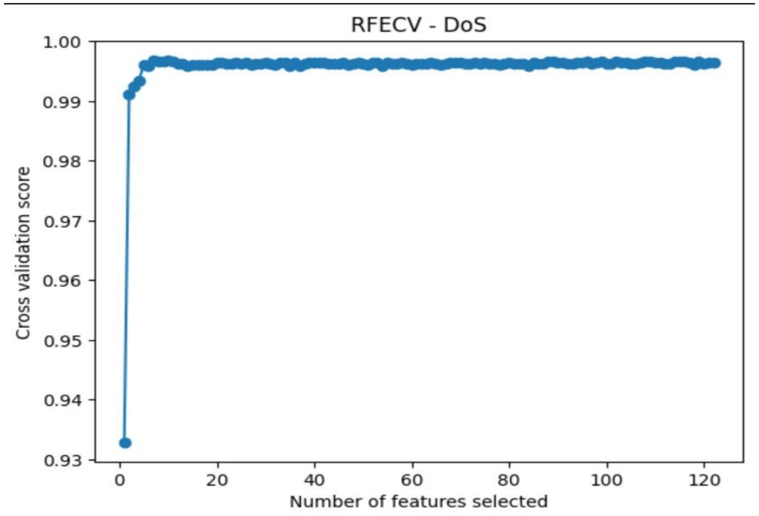

Comparison of Recall for RFE Models
Recall
1.00
0.98
0.96
0.94
0.92
0.90
DoS
Probe
R2L
U2R







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Key Insights

Efficient Intrusion Detection:

- Reduced features maintain performance.

Reliable DoS & Probe Detection:

- Systems can block malicious IPs quickly.

Challenges with R2L & U2R:

- Stealthy attacks need advanced methods or better features.

Future Directions for Network Security

Advanced Algorithms:

- Ensemble methods (Random Forest, XGBoost) or deep learning (LSTM).

Unsupervised Anomaly Detection:

- One-Class SVM, Isolation Forest.

Real-Time Systems:

- Test model speed and scalability in live networks.

Continuous Learning:

- Online learning for evolving threats.

Conclusion:

Summary:

- Built an ML pipeline: preprocessing, feature selection, training, evaluation.
- Demonstrated efficient detection with fewer features.
- Visualized results for clear communication.

Take-Home Message:

- ML enhances IDS, enabling efficient and accurate detection of network intrusions.