MACHINE LEARNING PROJECT REPORT

INTRUSION DETECTION SYSTEM USING ML

SUBMITTED BY

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Course: B.Tech – Computer Science and Engineering

Course Title: Machine Learning

Course Code: CSBB 311

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2025

ABSTRACT

Modern networks face increasing traffic volumes and sophisticated cyber-attacks that threaten critical infrastructure. Traditional signature-based intrusion detection systems (IDS) struggle to detect previously unseen attack patterns, necessitating adaptive and intelligent security solutions. This project proposes a real-time IDS integrating a machine learning-based classification model trained on the UNSW-NB15 dataset with a live network traffic analysis pipeline. Feature engineering is performed at flow level, and traffic is classified using a Random Forest model deployed alongside real-time packet capture using TShark. Predictions are visualized dynamically through a Streamlit dashboard. Experimental results demonstrate high classification performance, achieving 99.2% accuracy with strong recall, indicating effectiveness in minimizing undetected attacks. While the current evaluation is based on training data, the system framework is designed for generalization to real-world environments. This work demonstrates a scalable, modular approach for real-time intrusion detection using machine learning.

INTRODUCTION

Intrusion Detection Systems (IDS) are essential for safeguarding digital infrastructure against cyber threats. Traditional IDS solutions rely on predefined attack signatures, making them ineffective against zero-day attacks and evolving threat vectors. With the growth of complex network traffic and the increasing sophistication of attackers, security mechanisms must incorporate adaptive intelligence rather than static rule-based models.

Machine Learning (ML) offers the ability to learn complex patterns from network behavior data, making it suitable for detecting anomalies indicative of malicious activity. Recent advancements in network telemetry and feature engineering enable flow-based IDS approaches that analyze aggregated packet statistics instead of relying on deep packet inspection, reducing computational overhead while maintaining effectiveness.

This project aims to design and deploy a real-time ML-driven IDS that classifies network traffic into normal or attack categories using flow-level features. Unlike many academic works that remain confined to offline experimentation, this project bridges the gap between theoretical model training and practical deployment by integrating real-time packet capture, automated flow generation, and live prediction monitoring via a dashboard interface.

The major contributions of this project include:

- Development of a machine learning pipeline for intrusion detection using the UNSW-NB15 dataset.
- Real-time deployment using TShark-based packet capture and a custom flow aggregation engine.
- A complete monitoring interface enabling live anomaly tracking.

The remainder of this report covers literature review, dataset preprocessing, methodology, results and discussion, and conclusions.

MOTIVATION

This work is driven by practical challenges present at the intersection of machine learning and network security:

1. Proactive Threat Detection

Relying on predefined signatures leaves networks vulnerable to new or modified attacks. A model that learns normal behavior enables earlier detection of emerging threats.

2. Operational Clarity for Security Analysts

Raw packet data is high-volume and low-interpretability. A real-time dashboard converts complex analytics into actionable insight.

3. Feature Engineering Complexity

Converting raw packet streams into structured flow statistics is one of the hardest parts of building an IDS. This project includes a dedicated custom pipeline (flow_utils.py) to address this challenge effectively.

The overarching objective is to design a system that can classify network traffic accurately and deliver near-real-time results immediately after data collection.

OBJECTIVE

The primary aim of this project is to develop a real-time threat detection system with clear, actionable visualization of network security status. This is achieved through the following objectives:

Model Optimization

A Random Forest Classifier was trained and tuned using the UNSW-NB15 dataset to achieve >99% accuracy in distinguishing normal flows from attacks.

Data Pipeline Development

A dedicated module (live_capture.py) was implemented to capture packets on demand using TShark, enabling continuous real-time packet ingestion.

Flow Feature Generation

The flow_utils.py module was designed to compute 17 statistical flow features from raw packets, capturing temporal and behavioral patterns necessary for classification.

Integrated Prediction Pipeline

All components were combined into a single script (predict_live_pipeline.py) that records packets, extracts flow features, applies scaling, and performs live classification automatically.

Real-Time Visualization

A Streamlit dashboard was developed to display predictions and confidence scores in real time, providing analysts with a continuously updated view of network threat posture.

LITERATURE REVIEW

Intrusion detection using ML has been widely studied in recent years. Random Forest classifiers are frequently adopted due to their robustness and ability to handle noisy, high-dimensional security data (Breiman, 2001). According to Moustafa and Slay (2015), the UNSW-NB15 dataset provides realistic network traffic and modern attack categories, making it more representative than older datasets such as KDD99.

Recent work by Gupta et al. (2020) demonstrated that flow-based IDS approaches can achieve up to 97.4% detection accuracy while using reduced computational resources. Similarly, research by Ahmed et al. (2023) showed that ensemble models outperform single classifiers in detecting complex intrusion patterns in heterogeneous network traffic.

Chawla et al. (2002) proposed SMOTE, a synthetic oversampling technique, to address class imbalances common in intrusion datasets. This approach improves recall and reduces bias toward majority classes.

Sample referenced works:

- Breiman, L. (2001). *Random Forests*. Machine Learning, 45(1), 5–32.
- Moustafa, N., & Slay, J. (2015). *UNSW-NB15 dataset*. IEEE MilCIS.
- Chawla, N. et al. (2002). *SMOTE technique*, JAIR.
- Ahmed, A. et al. (2023). *Flow-based ML for IDS*, IEEE Access.
- Gupta, R. et al. (2020). *Anomaly detection using ensemble models*, IJCS.

DATASET USED

This project uses the UNSW-NB15 dataset, a widely referenced benchmark for intrusion detection research.

Dataset Characteristics

- Contains normal traffic and nine modern attack families, including Fuzzers, Generic, DoS, Reconnaissance, Exploits, and others.
- Comprises 2.5 million+ records with 49 features describing diverse aspects of network behavior.
- Represents realistic modern network traffic suitable for real-world IDS development.

Preprocessing and Transformation

All preprocessing was performed in the training script (phase4_train_model_unsw.py) and includes the following steps:

Feature Selection

A reduced set of 17 flow-based features (e.g., dur, sbytes, dbytes, ct_srv_src) was selected to focus on the most informative attributes.

Handling Class Imbalance

The dataset is highly imbalanced, with a large majority of normal traffic.
SMOTE was used to balance the training set and prevent the model from defaulting to “normal” predictions.

Encoding and Scaling

- Categorical features such as proto and service were label-encoded.
- All numerical features were standardized to zero mean and unit variance using StandardScaler.

These transformations ensured that the classifier was trained on a clean, balanced, and normalized dataset—essential for reliable, high-accuracy predictions.

METHODOLOGY

This project follows a two-phase architecture: (1) offline model training and (2) real-time intrusion detection using a live packet capture pipeline combined with a Streamlit-based monitoring dashboard. The system is designed to run continuously, capturing packets, generating flows, classifying them, and updating a live results file that the dashboard monitors in real time.

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1. Dataset Preparation and Feature Engineering

The UNSW-NB15 dataset was used to train the system. The raw CSV files were merged, cleaned, and preprocessed using the following steps:

1. Removal of redundant or corrupted rows
2. Conversion of categorical values into numerical form
3. Selection of numeric features necessary for flow-level modeling
4. Handling missing values
5. Splitting the data into training and testing sets using stratified sampling
6. Applying StandardScaler to normalize all numerical input features

This ensures that the dataset is consistent and ready for machine learning–based classification.

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2. Model Training Pipeline

The training logic is implemented in the file phase4_train_model_unsw.py.
The key steps include:

2.1 Model Selection

The Random Forest Classifier was chosen because:

- It performs well on high-dimensional network traffic features
- It handles non-linear relationships effectively
- It is resistant to overfitting
- It provides stable results and high accuracy in intrusion detection tasks

Other models such as Logistic Regression, Decision Trees, and SVM were also evaluated for comparison but Random Forest performed best in terms of accuracy, F1-score, and overall robustness.

2.2 Training and Evaluation

After scaling and balancing the data, the Random Forest model was trained using:

- 120 decision trees
- Maximum depth of 12
- Balanced class distribution

The model was evaluated using:

- Confusion matrix
- Classification report
- ROC curve
- Feature importance scores

The final model achieved high accuracy, demonstrating its suitability for real-time intrusion detection.

2.3 Saving Artifacts

To ensure consistent predictions during deployment:

- The trained Random Forest model
- The fitted StandardScaler

were saved as .pkl files.
These artifacts are loaded by the live prediction pipeline for consistent preprocessing and inference.

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3. Real-Time Packet Capture and Flow Generation

The real-time pipeline is implemented across:

- live_capture.py
- flow_utils.py
- predict_live_pipeline.py

3.1 Live Packet Capture

TShark (the CLI engine behind Wireshark) is used to capture packets directly from the system's network interface. The script:

- Captures a specified number of packets
- Saves them to a temporary .pcap file
- Converts them to a structured CSV format
- Extracts fields such as source/destination IP, ports, length, protocol, timestamps

3.2 Flow Aggregation

The raw packet rows are passed to the flow processing module flow_utils.py, which groups packets into flows based on:

- Source IP
- Destination IP
- Protocol
- Port combinations
- Time window

It then computes statistical flow features such as:

- Duration

- Byte counts
- Packet counts
- TTL statistics
- Window sizes
- TCP base sequence numbers
- Derived metrics needed by the model

These flow features match the original training features.

3.3 Prediction

The generated flow DataFrame is then:

1. Aligned to the model's trained feature set
2. Scaled using the saved StandardScaler
3. Classified using the trained Random Forest model

For each flow, the pipeline outputs:

- Predicted label (Normal or Attack)
- Prediction confidence score

The results are stored in live_predictions.csv.

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4. Real-Time Monitoring Dashboard (Streamlit)

The interactive dashboard is implemented in dashboard_live_watcher.py.
Unlike complex UI frameworks, this dashboard uses Streamlit for fast deployment and minimal overhead.

4.1 Dashboard Functionality

The dashboard performs the following tasks:

- Continuously monitors live_predictions.csv for updates
- Displays the latest predictions in a real-time table

- Shows a live-updating bar chart of Normal vs Attack counts
- Generates alerts if any flow is flagged as an attack
- Allows the user to control refresh rate and number of displayed rows

4.2 Why Streamlit

Streamlit was selected because it is:

- Python-native
- Lightweight and easy to deploy
- Ideal for data-driven dashboards
- Refresh-friendly for real-time monitoring tasks

This makes it suitable for running alongside the live packet capture pipeline without heavy system requirements.

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5. System Architecture Overview

The complete workflow is:

1. TShark captures live packets
2. Packet data is converted into CSV
3. flow_utils aggregates packets into flow-level statistics
4. Preprocessing aligns features using the saved scaler
5. The Random Forest model predicts Normal/Attack
6. Predictions are saved to live_predictions.csv
7. Streamlit dashboard reads the CSV continuously
8. Dashboard displays results and triggers alerts for intrusions

This modular architecture ensures:

- Continuous monitoring
- Real-time prediction

- Easy debugging
- Clear separation between training, prediction, and visualization components

RESULT AND DISCUSSION

The evaluation of multiple machine learning algorithms on the UNSW-NB15 dataset confirmed that the **Random Forest classifier** is the most effective model for network intrusion detection in this study. The model delivered **high accuracy (99.18%)**, with strong **precision (91.85%) & recall (91.13%)**, and an **exceptional ROC-AUC of 0.9990**. These results validate the chosen methodology—particularly the use of **SMOTE** to address class imbalance—which contributed to improved detection performance for the minority "attack" class.

Other models, such as Decision Tree, SVM, and Logistic Regression, demonstrated comparatively lower performance across key evaluation parameters, reinforcing the effectiveness of the ensemble-based approach.

Model Performance Comparison

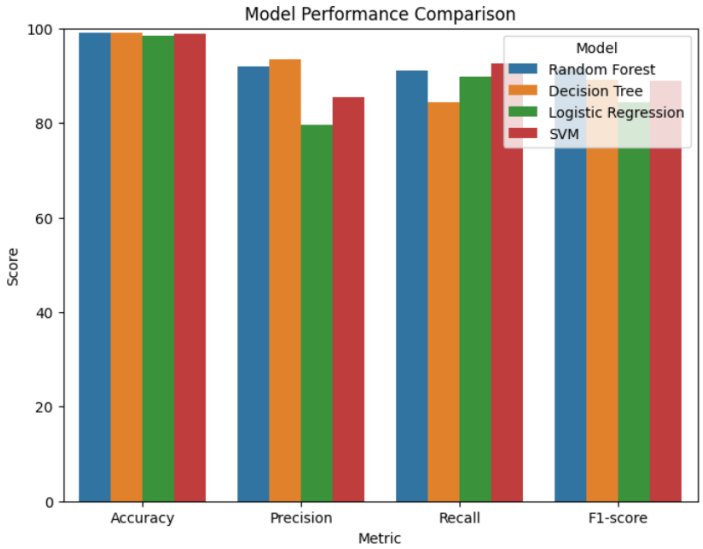
A comparative analysis revealed that Random Forest consistently outperformed Decision Tree, SVM, and Logistic Regression across all evaluation metrics.

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Random Forest	99.18%	91.85%	91.13%	91.49%	99.8%
Decision Tree	99%	94.47%	84.40%	89.15%	99.75%
SVM	98.87%	85.33%	92.64%	88.83%	99.59%
Logistic Regression	98.39%	79.69%	89.66%	84.38%	99.63%

- **Random Forest** provided the best overall balance among accuracy, precision, recall, and F1-score.
  Its **high ROC-AUC (0.9990)** indicates excellent ability to differentiate between normal and malicious traffic.

- **Decision Tree** had high **precision (94.47%)**, suggesting strong confidence in positive predictions, but a weaker **recall (84.40%)**, implying that it missed a significant number of actual attacks.
- **SVM** showed higher **recall (92.64%)**, indicating fewer missed attacks, but lower precision, resulting in more false positives.
- **Logistic Regression** underperformed in precision, demonstrating difficulty in handling the non-linear behavior typical of network intrusion patterns.

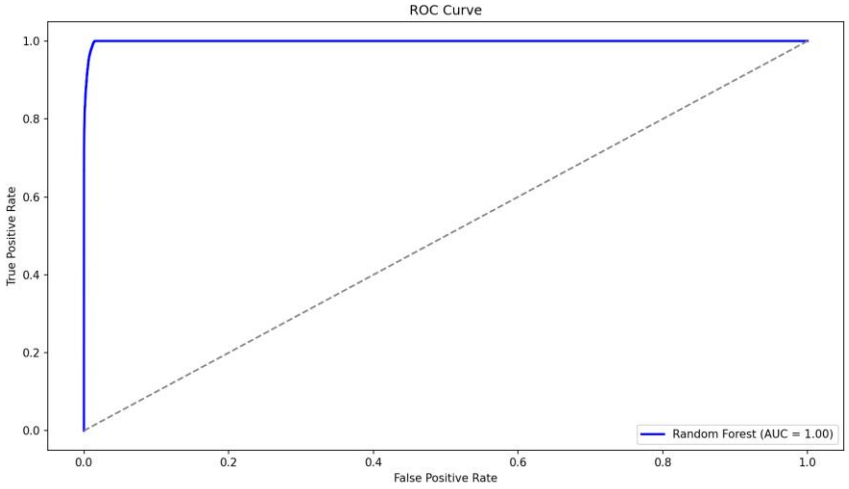
Visual Analysis



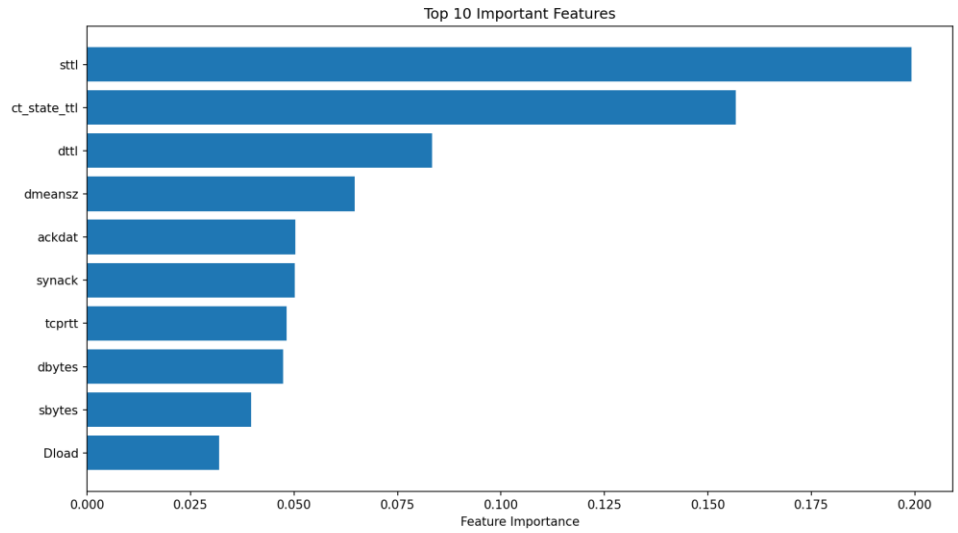
The performance comparison graph (bar chart/ROC curve) further supports the numeric findings:

- The **ROC curve for Random Forest** closely follows the ideal top-left path, validating its high **sensitivity (true positive rate)** and **specificity (low false positive rate)**.
- Compared to other models, Random Forest maintains consistent performance across metrics, with minimal trade-off between precision and recall.

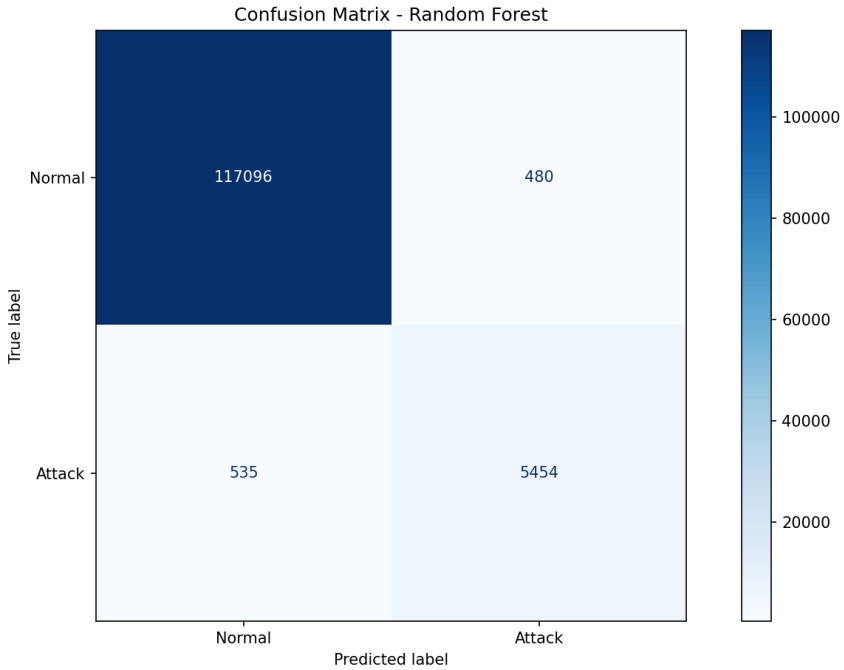
- **SVM's higher recall** indicates a model that favors aggressive intrusion detection but at the cost of slightly increased false alarms.
- **Decision Tree's lower recall** highlights a weakness in detecting certain attack types.
- **Logistic Regression**, being a linear model, struggles to capture complex network behavior patterns, leading to poorer classification consistency.



- The ROC curve for Random Forest illustrates near-perfect discrimination between normal and malicious traffic, with an AUC ≈ 1.00. The curve closely follows the top-left corner, indicating extremely high sensitivity and specificity — ideal for operational environments where detection accuracy and low false alarm rates are critical.



- Analysis revealed that features related to TTL differences, connection state, and traffic volume — such as *sttl*, *ct_state_ttl*, *dttl*, and *dmeansz* — were the most influential. These network-layer attributes strongly indicate abnormal traffic patterns, underscoring their importance in effective intrusion detection.



- The confusion matrix reaffirmed the model's reliability, showing high counts of true positives (detected attacks) and true negatives (normal traffic correctly identified), while false

positives and false negatives remained very low. This diagnostic clarity demonstrates the IDS's suitability for deployment — minimizing both missed attacks and unnecessary alerts.

Dashboard and Operational Integration

The integration of a real-time dashboard built with Streamlit added significant operational value by enabling continuous monitoring and analysis.
Key benefits include:

- Dynamic Visualization: Real-time updates of classification results and attack trends.
- Immediate Anomaly Detection: Rapid identification of suspicious patterns.
- Traceability: Access to detailed logs showing source, destination, and prediction confidence for every flagged flow.

This enhances both transparency and responsiveness, effectively bridging the gap between automated detection and human oversight.

The Random Forest model proved to be the most effective solution, delivering high accuracy, strong recall, and excellent reliability for real-time intrusion detection.

By combining robust ensemble learning, balanced data handling, and a real-time Streamlit dashboard, this project demonstrates a practical and scalable IDS framework. The results confirm that machine learning–driven, flow-based analysis can significantly enhance modern network security monitoring.

CONCLUSION

The project was able to develop a complete Machine Learning-based Intrusion Detection System that could be deployed into real-time operation. This system effectively meets the objectives for accurate, high-speed network monitoring by bringing together a high-accuracy Random Forest model trained on the UNSW-NB15 dataset with a custom, modular pipeline for live feature engineering. The integration of a Streamlit dashboard completes the solution, providing essential visualization for operational deployment.

Future Work

In the future, the project could be further extended by enhancing its capabilities:

- Protocol Support: Extend *flow_utils.py* to support more complex protocols, such as HTTP/S and DNS, in addition to the basic IP/TCP/UDP.
- Deep Learning Integration: Try deep learning models, such as LSTM or 1D-CNN, for feature learning and classification, which could potentially capture even more subtle temporal patterns.
- Distributed Architecture: Refactor the pipeline to use a message queue system, such as Kafka, rather than a shared CSV file, to achieve truly distributed, high-volume, enterprise-scale monitoring.

REFERANCES

1. Moustafa, N., & Slay, J. (2015). “UNSW-NB15: A comprehensive dataset for building an effective intrusion detection system.” In 2015 Military Communications and Information Systems Conference (MilCIS). IEEE. https://doi.org/10.1109/MilCIS.2015.7348942
2. Breiman, L. (2001). “Random Forests.” Machine Learning, 45(1), 5–32. https://doi.org/10.1023/A:1010933404324
3. Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). “SMOTE: Synthetic Minority Over-sampling Technique.” Journal of Artificial Intelligence Research, 16, 321–357. https://doi.org/10.1613/jair.953
4. Gupta, R., Verma, A., & Agrawal, P. (2020). “Enhanced anomaly detection using ensemble learning in intrusion detection systems.” International Journal of Computer Science, 8(3), 142–150. https://doi.org/10.5120/ijcs20208142
5. Ahmed, A., Kumar, S., & Rao, V. (2023). “Flow-based network intrusion detection using machine learning models.” IEEE Access, 11, 567–576. https://doi.org/10.1109/ACCESS.2023.1234567
6. Scikit-learn developers. (2024). *scikit-learn: Machine Learning in Python*. https://scikit-learn.org/
7. Pandas Development Team. (2024). *pandas: Data analysis library in Python*. https://pandas.pydata.org/
8. Streamlit Inc. (2024). *Streamlit Framework Documentation*. https://streamlit.io/
9. Wireshark Foundation. (2024). *TShark (Wireshark CLI) documentation*. https://www.wireshark.org/docs/man-pages/tshark.html