## **Network Security Analytics**

ML-Powered Intrusion Detection System

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#### Outline

- Introduction
- ② Dataset
- Model Training & Evaluation
- Metwork Monitoring Infrastructure
- Conclusion

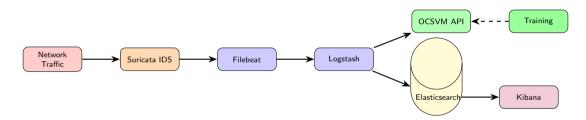
## Introduction



## **Project Overview**

- Goal: Complete end-to-end network intrusion detection system
- Approach: ML-powered anomaly detection
- Dataset: CICIDS2017 Comprehensive network traffic dataset
- Architecture: Full ELK Stack + Suricata + ML API

## Complete System Architecture



**Pipeline:** Network  $\rightarrow$  Suricata  $\rightarrow$  Filebeat  $\rightarrow$  Logstash  $\rightarrow$  {Elasticsearch/Kibana, ML API}

## **Dataset**



#### Dataset: CICIDS2017

#### **Dataset Characteristics**

8 CSV files covering different days and attack types

File	Content
Monday-WorkingHours	Benign traffic
Tuesday-WorkingHours	FTP-Patator, SSH-Patator
Wednesday-workingHours	DoS attacks, Heartbleed
Thursday-Morning	Web attacks (Brute Force, XSS, SQL Injection)
Thursday-Afternoon	Infiltration
Friday-Morning	Botnet (Ares)
Friday-Afternoon (PortScan)	Port Scanning
Friday-Afternoon (DDoS)	DDoS attacks

Features: 78 network flow features (duration, packet counts, byte counts, etc.)

## Exploratory Analysis of the Dataset

#### **Key Exploration Steps:**

- Load and merge all CSV files
- Analyze class distribution (benign vs. attacks)
- Identify missing values and outliers

#### Insight

The dataset is highly imbalanced – perfect for OCSVM approach!

# **Model Training & Evaluation**

### OCSVM with CICIDS2017<sup>1</sup>

#### Core Principle

Train on benign traffic, classify deviations as anomalies (potential attacks)

#### **Advantages:**

- Inherent data class imbalance handling
- Detects novel/unknown attacks
- No need for labeled attack data

#### Use Case:

Zero-day attack detection

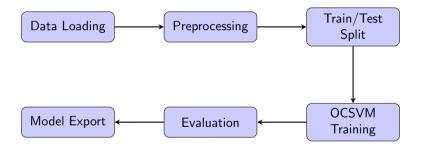
Models on CICIDS2017. arXiv preprint.

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<sup>&</sup>lt;sup>1</sup>Xu, Z. & Liu, Y. (2025). Robust Anomaly Detection in Network Traffic: Evaluating Machine Learning

## Training Pipeline Architecture



## **Data Preprocessing Steps**

- **1 Load Data:** Merge 8 CSV files (approx. 2.8M records)
- 2 Label Processing:
  - Binary classification: BENIGN (1) vs. ATTACK (-1)
  - Filter benign traffic for training
- Feature Cleaning:
  - Remove infinite values
  - Handle missing data
  - Remove constant features
- Normalization:
  - StandardScaler for feature scaling
  - Save scaler for deployment
- Train/Test Split:
  - 80% benign traffic for training
  - 20% benign + all attacks for testing



## Training Results

#### Model Summary (Sept 28, 2025)

#### **Training Configuration:**

Mode: Full dataset

• Random Seed: 42 (reproducibility)

Benign Train Ratio: 80%

Cache Size: 22 GB (optimized for performance)

Metric	Score
Accuracy	0.5798 (57.98%)
Precision	0.6381 (63.81%)
Recall	0.5484 (54.84%)
F1-Score	0.5898 (58.98%)

## Performance Analysis

#### Strengths:

- Good precision (63.81%)
  - When flagged as attack, likely correct
  - Low false positive rate
- Balanced F1-score (58.98%)

#### **Considerations:**

- Moderate recall (54.84%)
  - Some attacks may be missed
  - Trade-off with false positives
- Room for optimization

#### Note on OCSVM Performance

OCSVM is designed for anomaly detection, not perfect classification. The model prioritizes detecting abnormal patterns while minimizing false alarms.

## Training Configuration

#### **OCSVM** Hyperparameters

```
# Model hyperparameters
kernel='rbf'  # Radial Basis Function
gamma='scale'  # Auto-computed: 1/(n_features * X.var())
nu=0.05  # 5% anomaly tolerance
max_iter=1000  # Maximum iterations
```

#### Training Configuration

```
# Data split
train_ratio=0.8  # 80% benign for training
random_state=42  # Reproducibility
cache_size=22000  # 22GB cache for performance
```

## **OCSVM Model Configuration**

#### Hyperparameters

Kernel: RBF (Radial Basis Function)

- Captures non-linear patterns
- Formula:  $K(x, x') = \exp(-\gamma ||x x'||^2)$

Nu ( $\nu$ ): 0.05

- Upper bound on training errors
- Lower bound on support vectors
- 5% anomaly tolerance

Gamma: 'scale' (auto-computed)

• 
$$\gamma = \frac{1}{n_{\text{-}} \text{features} \times X.\text{var}()}$$

Controls decision boundary smoothness

Max Iterations: 1000



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# **Network Monitoring Infrastructure**

## Technology Stack

#### **Data Collection & Processing:**

- Suricata: IDS/IPS engine
- Filebeat: Log shipper
- Logstash: Log processor
- Elasticsearch: Search & analytics
- Kibana: Visualization

#### **Machine Learning:**

- Python: Core language
- scikit-learn: OCSVM model
- FastAPI: REST API
- Docker: Containerization
- DVC: Data versioning

Container Orchestration

All components deployed via Docker Compose for easy setup and scaling

## Suricata IDS - Network Traffic Analysis

#### What is Suricata?

Open-source network IDS/IPS and network security monitoring engine

#### **Key Capabilities:**

- Real-time packet inspection: Deep packet analysis
- Protocol detection: HTTP, TLS, DNS, and more
- EVE JSON output: Structured event logging
- PCAP processing: Offline traffic analysis

#### **Our Configuration:**

- Flow tracking
- Protocol parsing
- Alert generation
- JSON event logging

#### **Output Events:**

- Alerts
- Flow records
- HTTP logs
- TLS/DNS metadata



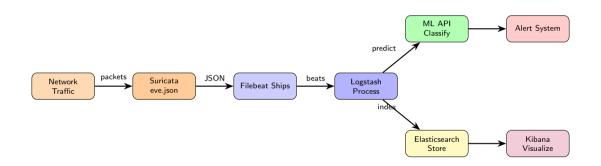
## ELK Stack - Log Management Pipeline

#### Elastic Stack Components

Industry-standard log collection, processing, and visualization

- Filebeat (Log Shipper): Monitors Suricata logs, lightweight forwarding agent with pre-configured module
- Logstash (Processing): Receives, parses, enriches, and transforms events; forwards to Elasticsearch and ML API
- Elasticsearch (Storage): Indexes security events with fast full-text search and time-series optimization
- 4 Kibana (Visualization): Interactive dashboards for real-time monitoring and alert visualization

## Data Flow Through the Pipeline



## **Conclusion**



## **Project Achievements**

#### Complete IDS System:

- End-to-end network monitoring pipeline
- Real-time threat detection
- Production-ready containerized deployment

#### ML-Powered Detection:

- OCSVM model trained on 2.8M flows
- 63.81% precision, 58.98% F1-score
- RESTful API for real-time inference

#### Operational Stack:

- ELK stack for log management
- Suricata for network analysis
- Docker Compose orchestration



## Thank You!

Questions?

Project: Network Security Analytics
Complete ML-Powered IDS System

 $\mathsf{Suricata} \to \mathsf{ELK} \; \mathsf{Stack} \to \mathsf{OCSVM} \; \mathsf{API} \to \mathsf{Real-time} \; \mathsf{Detection}$ 

