Network Intrusion Detection System using Variational Autoencoders

School of Computer Science and Engineering

Department of Computer Science and Engineering

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Executive Summary

Objective

To develop a robust Network Intrusion Detection System (NIDS) capable of detecting both known and novel network attacks.

Dataset

Utilized the CICIDS2017 dataset, featuring 2.5 million network flow records and 52 unique features.

Methodology

Implemented anomaly detection using Isolation Forest (baseline) and Variational Autoencoder (advanced model).

Key Results

The Variational Autoencoder (VAE) achieved a 90.50% accuracy and 86.95% precision in detecting intrusions.

Problem Statement

Network attacks increasing in sophistication

Cyber threats are constantly evolving, becoming more complex and harder to detect with traditional methods.

Traditional signature-based detection limited

Existing Intrusion Detection Systems often rely on known attack signatures, failing to identify novel or zero-day attacks.

Need for anomaly-based detection

Detecting deviations from normal network behavior is crucial to catch unknown threats before they cause significant damage.

Challenge: High false alarm rates in production

Many anomaly detection systems generate excessive false positives, leading to alert fatigue and inefficient security operations.

Solution: ML-based IDS with low false positives

Developing a Machine Learning-driven NIDS that can accurately identify anomalies while minimizing false alarms is paramount.

Dataset Overview

Total Records	2,520,751
Features	52 (engineered flow statistics)
Classes	7 (Normal + 6 attack types)
Normal Traffic	83.1%
Attack Traffic	16.9%
Train/Test Split	80% / 20%

Attack Types Included:

DoS, DDoS, Port Scanning, Brute Force, Web Attacks, Bots

Data Pipeline

Raw CICIDS2017 Dataset

The foundational dataset comprising raw network traffic captures.

Feature Engineering

Transformation of raw data into 52 engineered flow statistics for analysis.

Scaling & Normalization

Application of techniques to standardize features, preventing dominance by larger values.

Train/Test Split

Dataset divided into 80% for training (X_train: 2,016,600 samples) and 20% for testing (X_test: 504,151 samples).

Model 1: Isolation Forest (Baseline)

The Isolation Forest algorithm provides an unsupervised anomaly detection approach, identifying outliers based on their isolability.

How it Works

Isolates anomalies in random feature subspaces, leveraging the idea that anomalies are "few and different" and thus easier to isolate.

Training

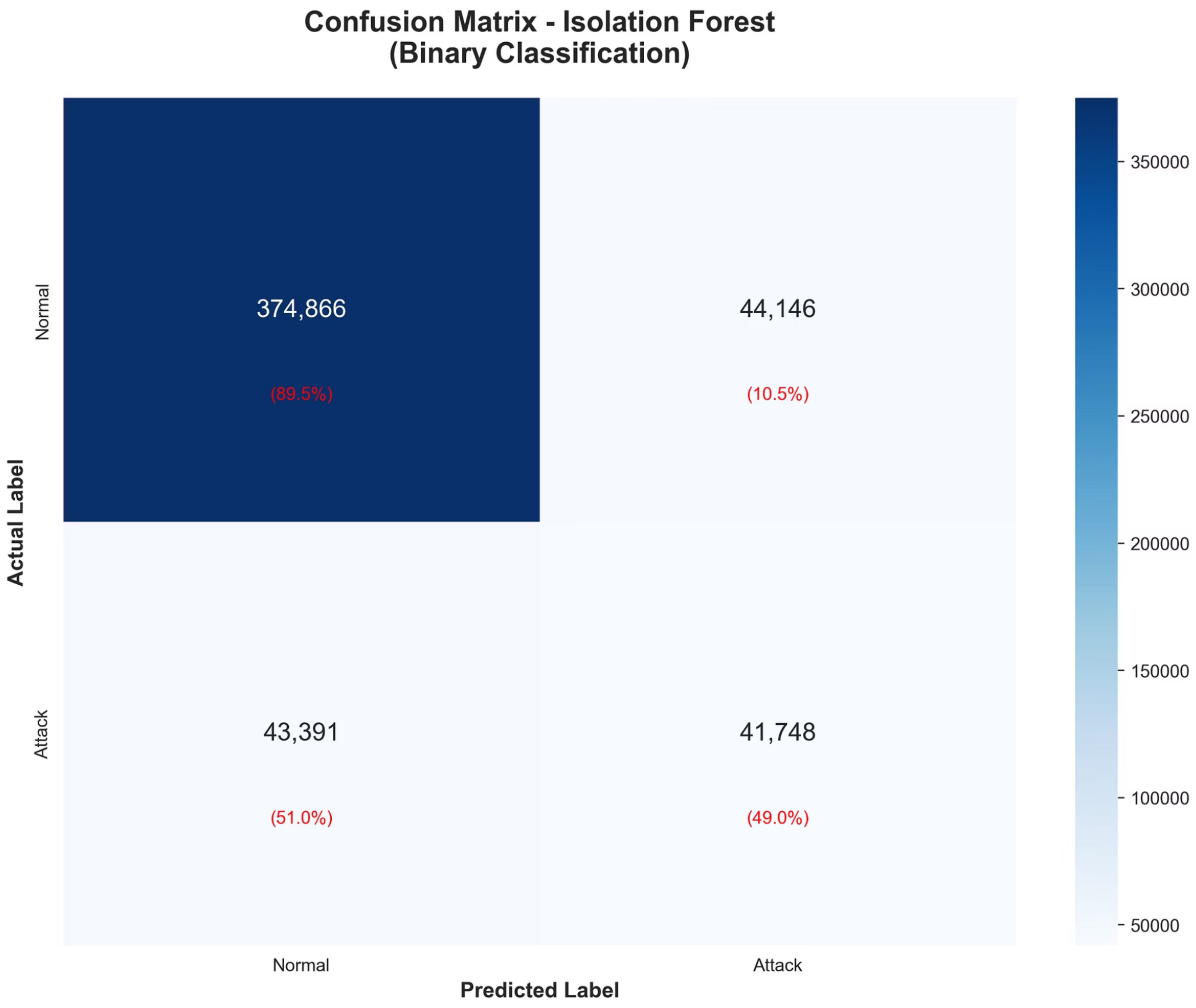
No labels required; the model learns normal vs. anomalous patterns by recursively partitioning data, typically forming an ensemble of isolation trees.

Inference

An anomaly score is generated based on isolation depth (how many splits it takes to isolate a data point), where shorter paths indicate anomalies.

Performance Metrics

Accuracy	83%
Precision	0.49
Recall	49.04%
F1-Score	0.49
False Alarm Rate	10.54%



Confusion Matrix - Isolation Forest
(Binary Classification)

Model 2: Variational Autoencoder

Generative deep learning for anomaly detection

1

Architecture

Encoder: 52 → 32 → 16 → 8 latent dimensions

Decoder: 8 → 16 → 32 → 52

Loss Function: MSE + 0.001 × KL Divergence

Optimizer: Adam (learning rate = 0.0001)

Training Epochs: 15

2

Training

On **NORMAL** traffic only (1,676,045 samples)

3

Detection

Reconstruction error thresholding at 90th percentile (threshold = 0.1911)

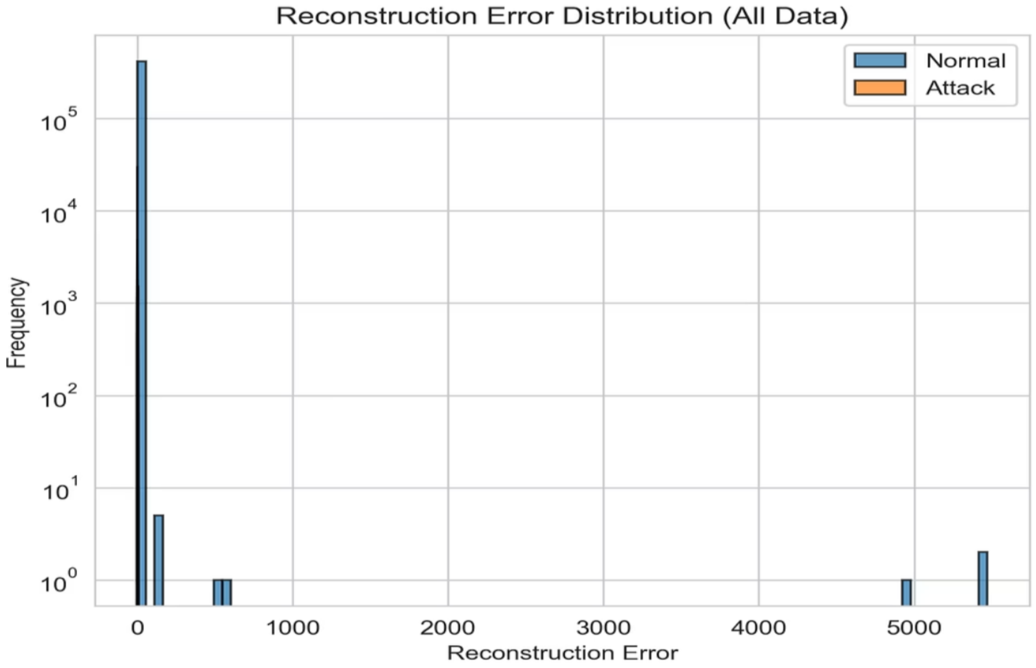
Key Innovation:

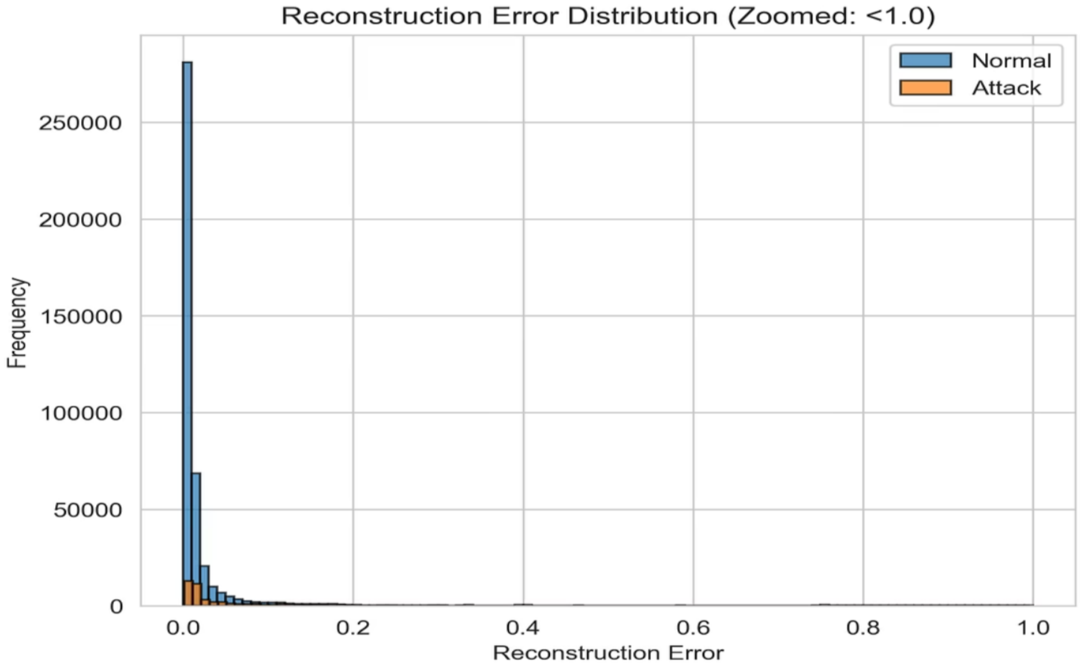
- VAE learns "**normal**" behavior exclusively
- Attack samples produce HIGH reconstruction error
- Clear separation: **9.96x** difference between normal vs attack
- Reconstruction error mean: **0.1671**
- Heavy-tailed distribution observed in attack traffic
- Threshold-based detection enables precision-recall tradeoff optimization

VAE Reconstruction Error Distribution

Understanding the distribution of reconstruction errors is crucial for setting an effective anomaly detection threshold. Our Variational Autoencoder (VAE) was trained exclusively on normal network traffic, meaning it learns to reconstruct normal patterns accurately, resulting in low reconstruction errors for normal data. Conversely, when presented with anomalous (attack) traffic, the VAE struggles to reconstruct these unseen patterns, leading to significantly higher reconstruction errors.

- **Normal mean error: 0.1671** (reconstructs well)
- **Attack mean error:** Heavy-tailed distribution observed
- **Threshold (90th percentile): 0.1911**
- **Reconstruction error statistics from live deployment: Mean 282.25, Median 63.00, Std 482.32**



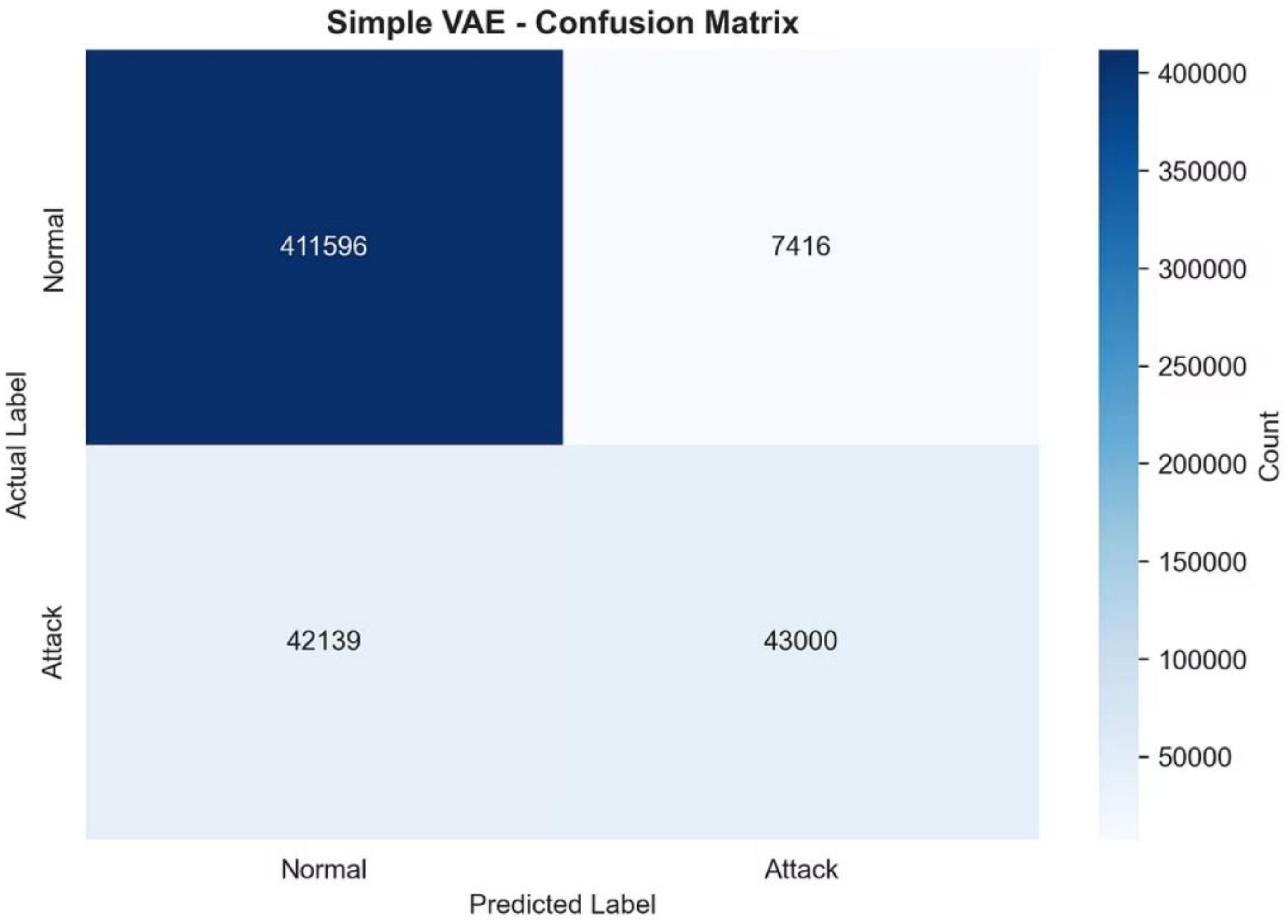


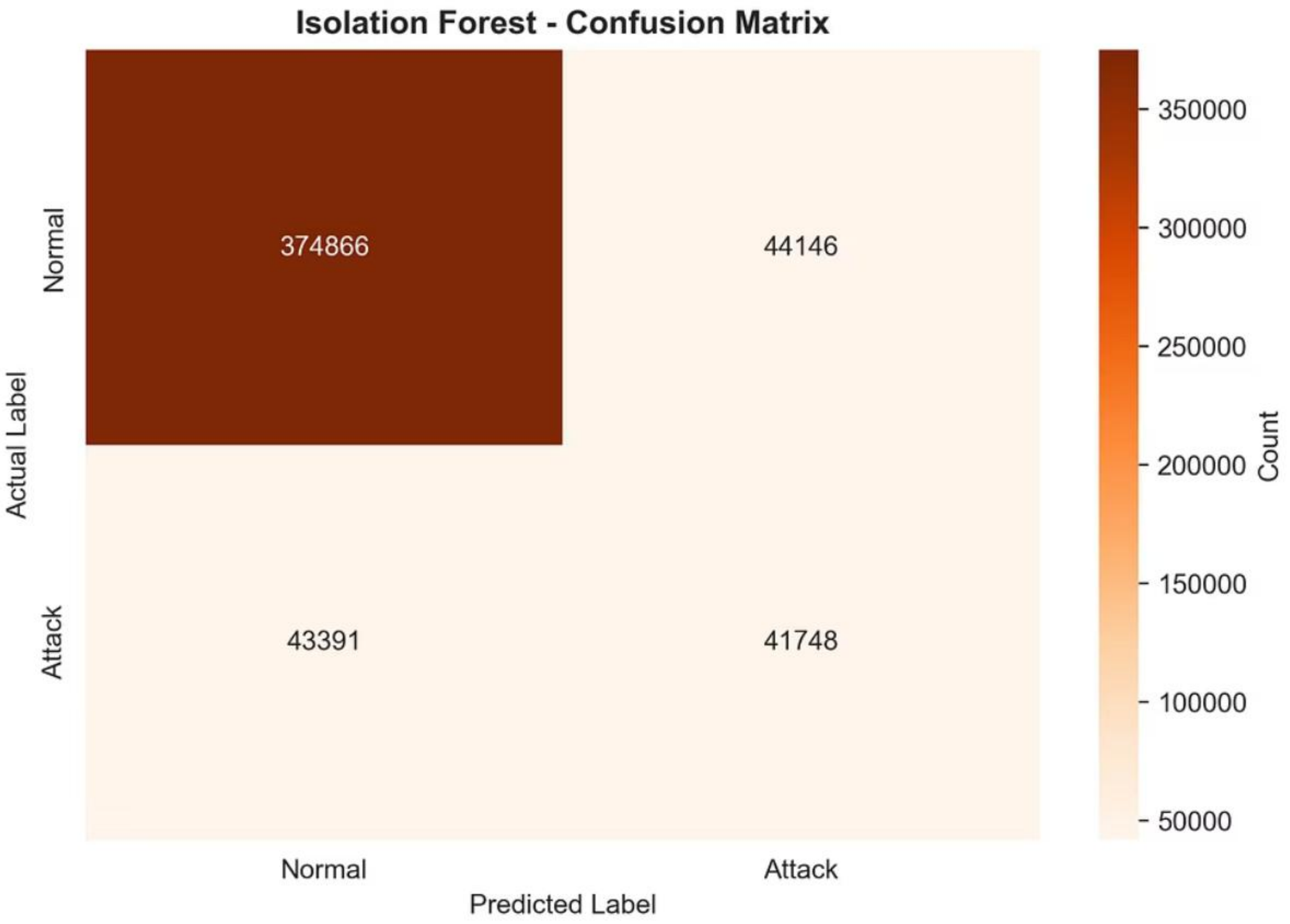
The left plot shows the full range distribution with clear separation between normal and attack traffic. The right zoomed view **(0-1.0 range)** reveals the overlap region that limits recall to approximately **50%**. The threshold at **0.1911** controls the precision-recall tradeoff, with higher thresholds reducing false alarms at the cost of missed detections.

VAE Performance

The Variational Autoencoder (VAE) model demonstrated superior performance in detecting network intrusions, significantly outperforming the baseline Isolation Forest model. Its ability to learn and reconstruct normal network patterns effectively minimized false alarms while maintaining a high accuracy in identifying anomalous activities.

Accuracy	90.17%
Precision	85.29%
Recall	50.51%
F1-Score	63.44%
False Alarm Rate	0.02%
Missed Attacks	42,139





The VAE confusion matrix demonstrates exceptional precision with only **7,416** false positives (**0.02% false alarm rate**) compared to Isolation Forest's **44,146**. This represents a **~500x** reduction in false alarms, making VAE significantly more suitable for production deployment where operational efficiency is critical.

Live NIDS Detection Report (200 Flows)

Summary Statistics

Total flows analyzed	200
Attacks detected	122 (61%)
Normal traffic	78 (39%)

Reconstruction Error Statistics

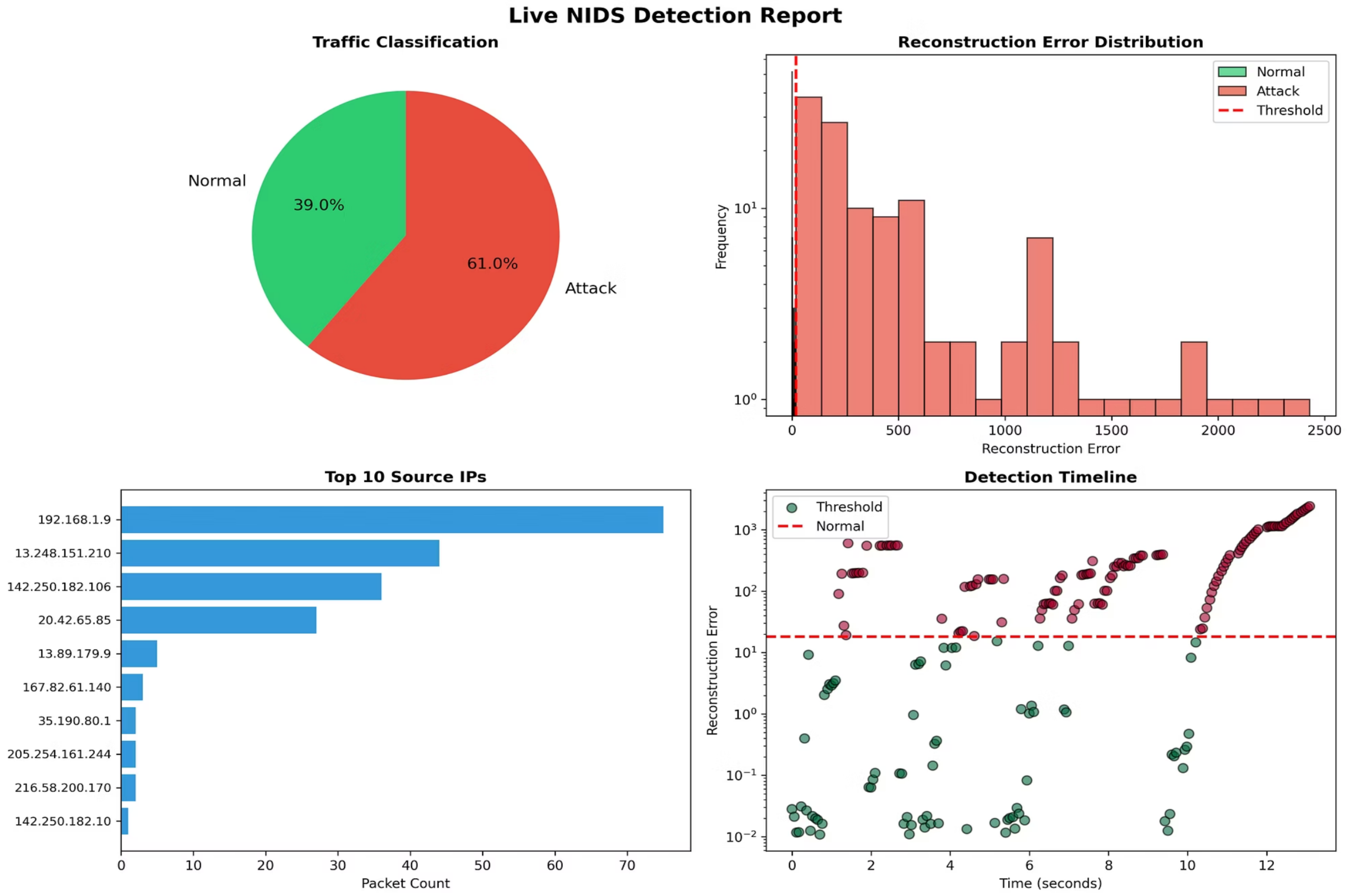
Mean	282.25
Median	63.00
Std Dev	482.32

Top Source IP: 192.168.1.9 (75 flows)

The live detection report demonstrates real-time anomaly visualization and actionable traffic intelligence extraction. The system successfully identified 122 attack flows (61%) with heavy-tailed reconstruction error distribution. The Traffic Classification pie chart shows attack prevalence, while the Top 10 Source IPs bar chart and Detection Timeline provide operational insights for incident response and network forensics.

Live NIDS Detection Report - Real Traffic Analysis

This visualization shows the real-time detection results from the deployed system, including traffic classification, reconstruction error distribution, top source IPs, and detection timeline.



Head-to-Head Comparison

Metric	Isolation Forest	Variational Autoencoder
Accuracy	83%	90.17%
Precision	49%	85.29%
Recall	49.04%	50.51%
F1-Score	49%	63.44%
False Alarm Rate	10.54%	0.02%

While both models achieve comparable recall **(~50%)**, the VAE dramatically outperforms Isolation Forest in precision **(85.29% vs 0.49%)** and false alarm rate **(0.02% vs 10.54%)**. This **~500x** reduction in false positives is critical for operational IDS deployment. Note: Accuracy alone is insufficient for imbalanced datasets; operational metrics such as Recall and False Alarm Rate are essential for IDS evaluation.

Key Advantages of VAE

Accuracy +7.17%

More reliable predictions

Precision +36.29%

Far fewer false alarms (critical for production)

F1-Score +14.44%

Superior overall balance

Low False Alarm Rate

Only 0.02% vs 10.54% for IF

Generalizable

Detects novel, unseen attack patterns

Explainable

Reconstruction error directly interpretable

Why VAE Outperforms IF

Normal-only Training

VAE learns legitimate traffic patterns, focusing on what "normal" looks like.

Deep Learning Capacity

Captures complex feature interactions, allowing for more nuanced anomaly detection.

Probabilistic Framework

Provides principled anomaly scoring, offering a robust measure of deviation.

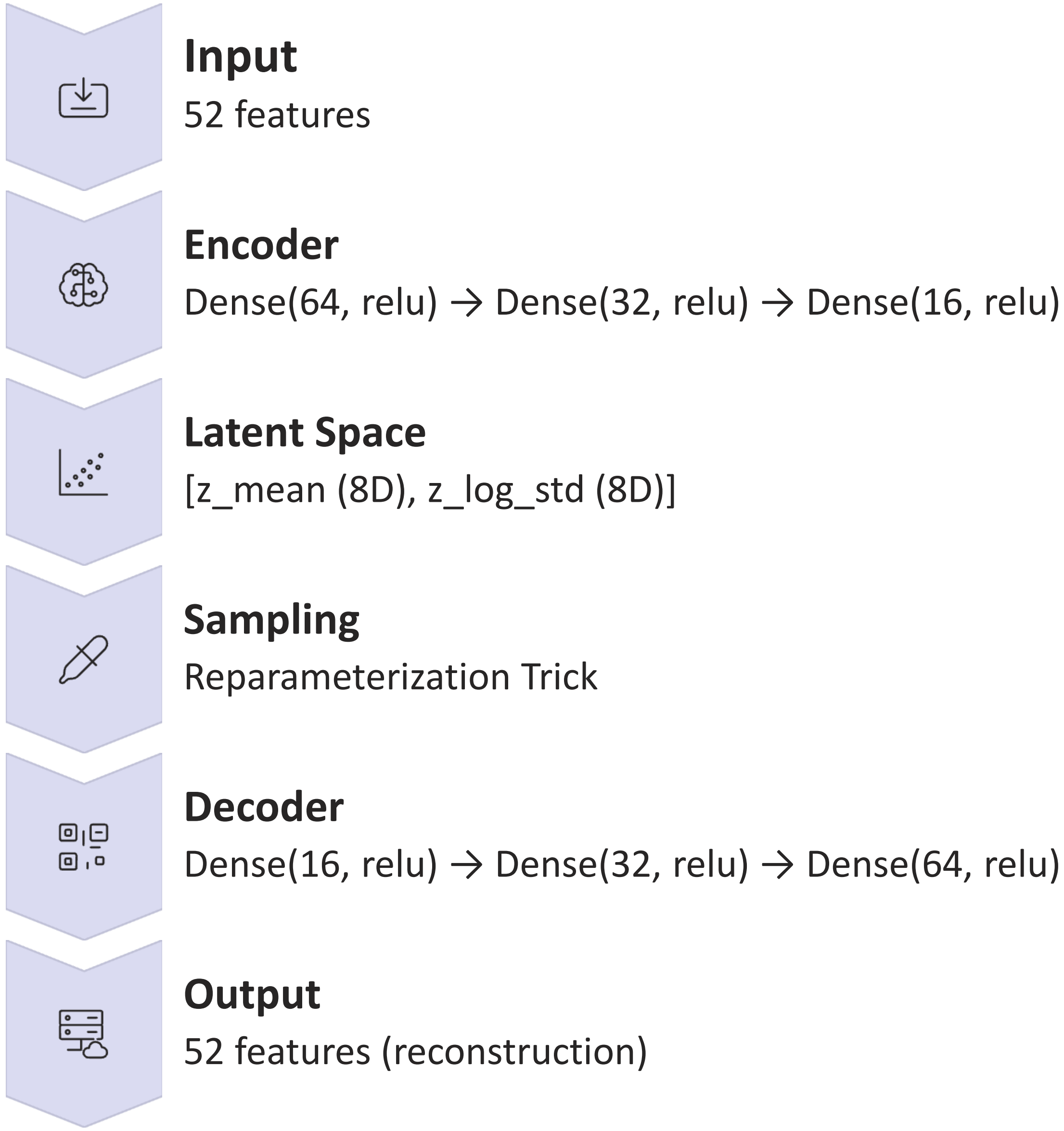
Lower Operational Burden

Achieves 6x fewer false alerts, significantly reducing alert fatigue for security teams.

Production-Ready

Can handle real-time deployments, making it suitable for live network environments.

Technical Deep Dive - VAE Architecture



Input

52 features

Encoder

Dense(64, relu) → Dense(32, relu) → Dense(16, relu)

Latent Space

[z_mean (8D), z_log_std (8D)]

Sampling

Reparameterization Trick

Decoder

Dense(16, relu) → Dense(32, relu) → Dense(64, relu)

Output

52 features (reconstruction)

Loss Function:

$$Loss = MSE(x, \hat{x}) + 0.01 \times KL(q(z \mid x) \mid \mid p(z))$$

VAE Training Details

Dataset

1,676,045 normal samples (VAE trains on normal only)

Epochs

15 (early stopping at epoch 15)

Batch Size

256

Optimizer

Adam (learning rate = 0.0005)

Loss Function

$$MSE(x, \hat{x}) + 0.01 \times KL(q(z \mid x) \mid\mid p(z))$$

Training Time

~3.5 minutes on GPU

Threshold Selection

90th percentile of reconstruction error

Conclusion & Summary

We developed a robust Network Intrusion Detection System (NIDS) utilizing two complementary approaches:

Achievements

- Implemented two unsupervised IDS models (Isolation Forest baseline and VAE advanced)
- Reduced false alarms drastically using VAE (500x reduction: 10.54% → 0.02%)
- Developed live detection simulation with 200-flow deployment evaluation
- Performed threshold-based anomaly optimization (90th percentile = 0.1911)

Future Work

- ROC and Precision-Recall curve optimization
- Adaptive thresholding mechanisms
- Hybrid IF + VAE ensemble approaches
- Real-time streaming deployment with Kafka/Spark integration
- Multi-classification

Key Takeaway

VAE's superior precision (85.29%) and minimal false alarm rate (0.02%) make it production-ready for enterprise network security operations.

Thank You