

CIC-IIoT-2025 Security Analysis

Machine Learning for Intrusion Detection in Industrial IoT

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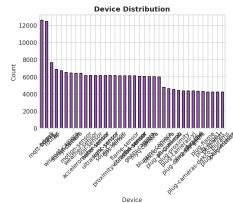
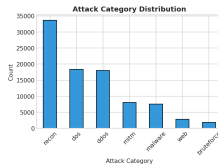
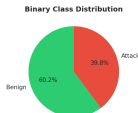
Agenda

- 1 Dataset Overview and Exploration
- 2 Anomaly Detection (Unsupervised)
- 3 Classification (Supervised)
- 4 Adversarial Machine Learning
- 5 Recommendations

Objective: Evaluate ML methods for IIoT intrusion detection and assess adversarial robustness

CIC-IIoT-2025 Dataset

Attribute	Value
Total Samples	227,191
Features	94
Attack Samples	90,391 (39.8%)
Benign Samples	136,800 (60.2%)
Attack Categories	7



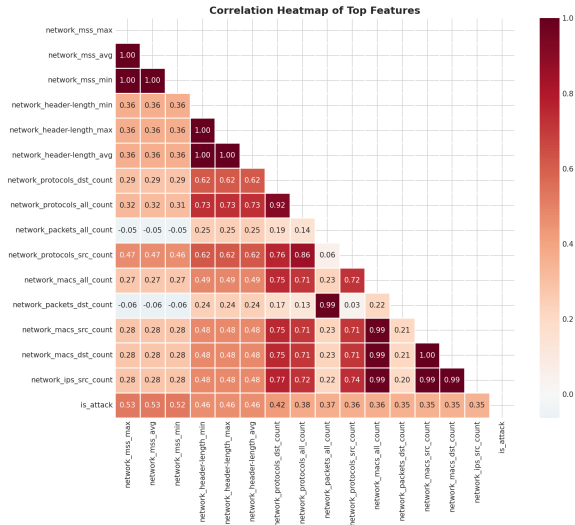
Categories: Reconnaissance, DoS, DDoS, MitM, Malware, Web, Brute Force

Key Discriminative Features

Top Correlated Features:

Feature	Corr.
network_mss_max	0.526
network_mss_avg	0.525
network_header-length_min	0.464
network_protocols_dst_count	0.423
network_packets_all_count	0.367

TCP MSS and protocol diversity are strong attack indicators



Anomaly Detection (Unsupervised)

Trained on benign traffic only – Detects zero-day attacks

Method	Approach
Isolation Forest	Tree-based isolation via random partitioning
One-Class SVM	Kernel-based boundary in feature space
Local Outlier Factor	Local density deviation detection

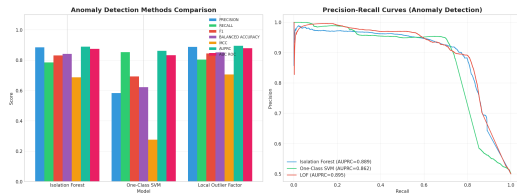
Evaluation Metric: AUPRC (Area Under Precision-Recall Curve) – robust for imbalanced detection

Anomaly Detection Results

Model	F1	AUPRC	MCC
Isolation Forest	0.832	0.889	0.688
One-Class SVM	0.693	0.862	0.276
LOF	0.844	0.895	0.705

Winner: Local Outlier Factor

Density-based methods excel on this dataset



Using labeled attack and benign samples

Method	Approach
Random Forest	Ensemble of decision trees with majority voting
Gradient Boosting	Sequential boosting with error correction
SVM (RBF Kernel)	Kernel-based non-linear separation

Terminology:

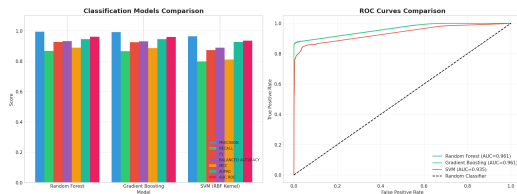
- **Astute Accuracy:** Performance on clean (non-adversarial) data
- **Robust Accuracy:** Performance under adversarial attack

Classification Results

Model	F1	MCC	AUC
Random Forest	0.927	0.890	0.961
Gradient Boosting	0.925	0.886	0.961
SVM (RBF)	0.874	0.811	0.935

Winner: Random Forest

All classifiers achieve >87% F1-score



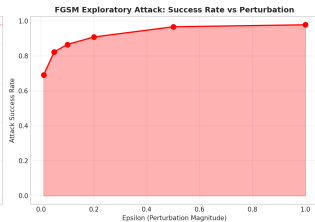
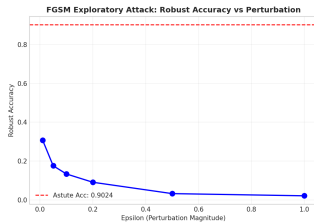
Adversarial ML: Exploratory Attack (FGSM)

Fast Gradient Sign Method – Perturbs test samples

$$x_{adv} = x + \epsilon \cdot \text{sign}(\nabla_x J(\theta, x, y))$$

ϵ	Robust Acc.
0.01	86.7%
0.05	26.0%
0.10	16.0%
0.50	3.5%

Linear SVM (Astute: 89.8%)



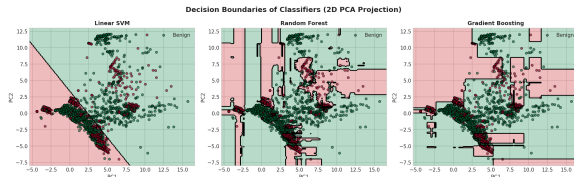
Adversarial ML: Causative Attack (Data Poisoning)

Label Flipping – Poisons training data to shift decision boundary

Attack Mechanism:

- Attacker corrupts training labels
- Model learns incorrect boundaries
- Attacks evade detection at inference

Poison Rate	Accuracy
0%	94.3%
10%	85.2%
20%	72.1%



Model Robustness Comparison ($\epsilon = 0.5$)

Model	Astute Acc.	Robust Acc.	Robustness Ratio
Linear SVM	90.2%	3.2%	3.6%
Random Forest	94.6%	3.8%	4.0%
Gradient Boosting	94.4%	34.0%	36.0%

Finding: Gradient Boosting retains 36% accuracy under FGSM attack
Linear models collapse to near-random performance

Summary: Best Models by Task

Task	Best Model	Key Metric
Zero-day Detection	Local Outlier Factor	F1 = 0.844, AUPRC = 0.895
Attack Classification	Random Forest	F1 = 0.927, AUPRC = 0.946
Adversarial Robustness	Gradient Boosting	36.0% robust acc.

Key Insight: No single model excels at all tasks – defense-in-depth required

Multi-Layer Defense Architecture:

- 1 **Layer 1 (LOF):** Zero-day attack early warning
- 2 **Layer 2 (Random Forest + Gradient Boosting):** Classification ensemble for accuracy and robustness
- 3 **Layer 3:** Input validation and adversarial training

Production Hardening:

- Implement adversarial training with augmented samples
- Regular model retraining with new threat intelligence
- Feature monitoring for distribution drift

Questions?

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