

# Analyzing IoT Vulnerabilities

A Longitudinal Study of CVE  
Disclosures and Exploitability Trends  
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# Introduction

- IoT devices have expanded across sectors, increasing security risks (Kumar & Fung, 2024)
- Common issues: weak authentication, poor encryption, delayed patches (Bonaventura et al., 2025)
- Focus: CVE trends, exploitability, and machine learning classification (Khanmohammadi & Khoury, 2022)

# Overview

The proliferation of IoT devices has introduced major cybersecurity challenges due to weak authentication, poor encryption, and delayed patching.

This study analyzes IoT vulnerability trends, time-to-exploitation, and develops a framework for automated vulnerability classification using statistical and machine learning approaches.

# The Role of CVE in IoT Security

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The Common Vulnerabilities and Exposures (CVE) framework plays a critical role in documenting security weaknesses across IoT ecosystems.



CVE assigns unique identifiers to vulnerabilities.



- These IDs standardize tracking, communication, and remediation.



- Organizations use CVEs to prioritize and coordinate security responses.

# What the Literature Reveals About CVEs

- CVE records often lack critical metadata.

- This gap leads to delays in security assessments and patch deployment.

- Metadata deficiencies impact vulnerability prioritization.

(Khanmohammadi & Khoury, 2022)

# Manual Processes and CNA Variability

Manual vulnerability disclosure and remediation introduce inconsistencies.

CVE Numbering Authorities (CNAs) differ in response times and coordination.

This variability complicates global vulnerability management.

(Lin et al., 2023)

# Rapid Exploitation and Need for CVD



Attackers often exploit newly disclosed vulnerabilities within days.



Speed of exploitation highlights the need for timely response.



Strengthening Coordinated Vulnerability Disclosure (CVD) frameworks is essential.



(Pauley et al., 2023)

## ML for CVE Classification

To address the limitations of manual vulnerability classification, researchers have proposed machine learning-based models for automating CVE analysis.

- Kota et al. (2024) introduced a semantic similarity-based ML model for CVE classification.

- The model achieved 72.1% accuracy in predicting security weaknesses from CVE descriptions.

- This approach enhances efficiency and scalability in vulnerability management.

# Aim of the Study

Analyze the evolution of IoT vulnerabilities, with a focus on:

Tracking and classification of vulnerabilities.

Identifying effective mitigation strategies.

Investigating the time gap between CVE disclosure and real-world exploitation.

Assessing trends in vulnerability severity and exploitability.

Classifying IoT security risks by device category: Consumer, Industrial, and Healthcare IoT.

# Research Questions



RQ1: How have IoT-related vulnerability disclosures, severity ratings, and exploitability patterns evolved over the past decade based on National Vulnerability Database (NVD) data?



RQ2: How accurately can supervised learning models (e.g., SVM and BERT-based NLP models) predict the likelihood of exploitability and automate the categorization of IoT vulnerabilities?



RQ3: How do threat intelligence feeds (e.g., CISA KEV, VirusTotal, IBM X-Force Exchange) contribute to tracking the progression of IoT vulnerabilities from disclosure to real-world exploitation?



RQ4: What is the average time between IoT vulnerability disclosure and the first recorded exploitation attempt, and how do different vulnerability repositories (e.g., Exploit-DB, Metasploit, Shodan, AttackerKB) contribute to monitoring this timeline?

# Research Objectives

- Analyze IoT vulnerability trends (2015–2025)

- Assess disclosure-to-exploitation time gaps

- Identify high-risk IoT categories

- Develop ML-based framework for exploitability prediction

# Data Sources

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- National Vulnerability Database (NVD)

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- CISA KEV Catalog

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- CVSS, CWE, CPE datasets

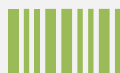
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- Future: VirusTotal, IBM X-Force Exchange

# Methodology Overview



Automated NVD pipeline  
(`nvd\_iot\_pipeline.py`)



IoT identification via  
keyword/vendor heuristics



Statistical analysis using GLM  
and MLM



Cross-referenced with KEV  
exploit data

# IoT Vulnerability Share (2015–2025)

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IoT CVEs account for ~18% of all CVEs ( $\approx 44,569$  of 247,189).

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## Exploitation Rates by Year (All CVEs)

- Exploitation rates remain below 0.2% overall but show spikes in 2020–2023.

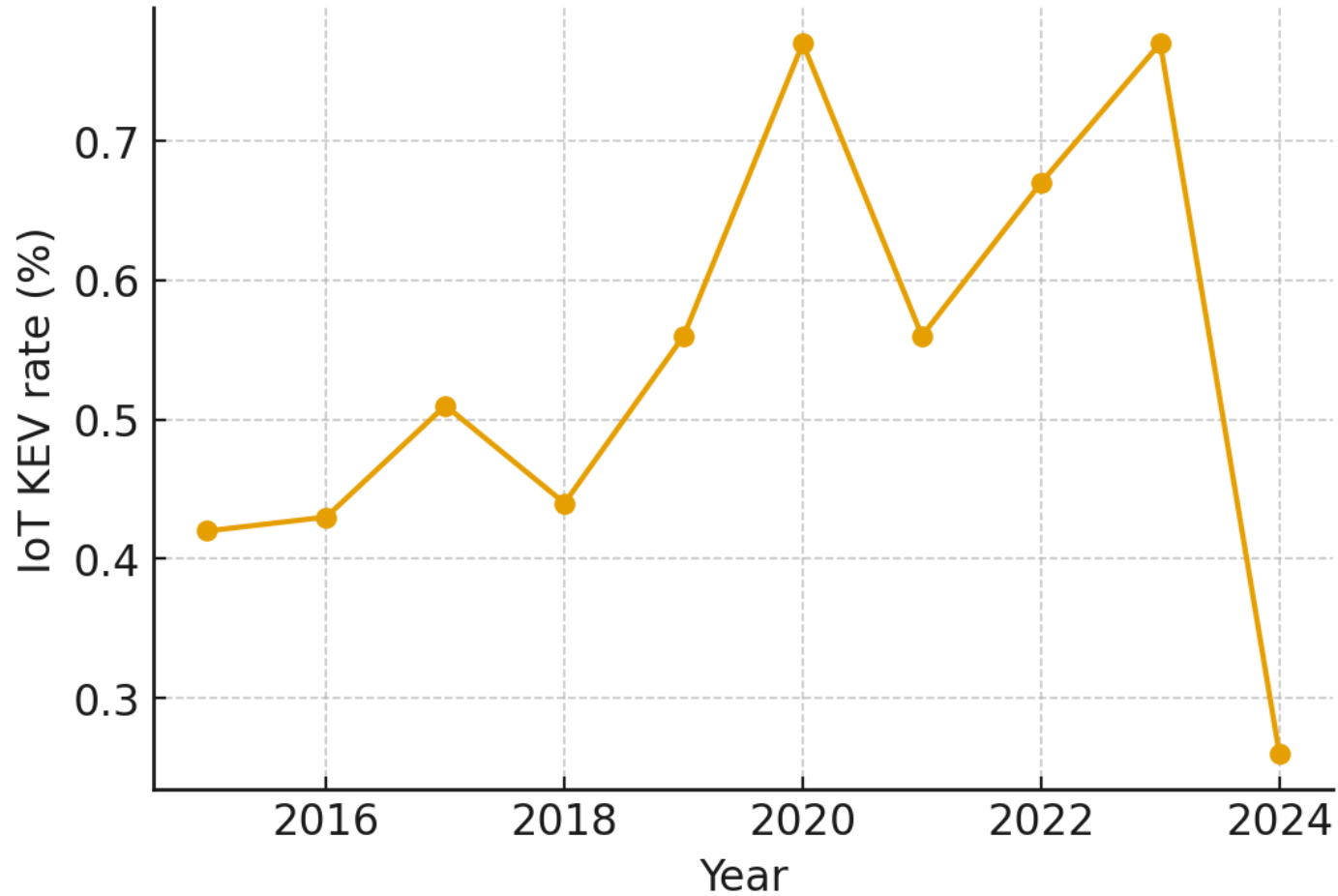


# IoT Exploitation by Year

- IoT exploitation 5–10× higher than general CVEs, peaking at 0.77% in 2020 and 2023.

Year	Total IoT CVEs	Exploited (KEV)	Exploitation Rate (%)
2015.0	713.0	3.0	0.42
2016.0	706.0	3.0	0.43
2017.0	5143.0	26.0	0.51
2018.0	3639.0	16.0	0.44
2019.0	3714.0	21.0	0.56
2020.0	3643.0	28.0	0.77
2021.0	4444.0	25.0	0.56
2022.0	3713.0	25.0	0.67
2023.0	4011.0	31.0	0.77
2024.0	7042.0	18.0	0.26

# IoT CVE Exploitation Rate by Year



# GLM Statistical Results



IoT (TRUE): OR  $\approx 2.8 \times 10^8$  ( $p < 0.001$ )



Severity (Critical): OR  $\approx 20.3$  ( $p = 0.006$ )

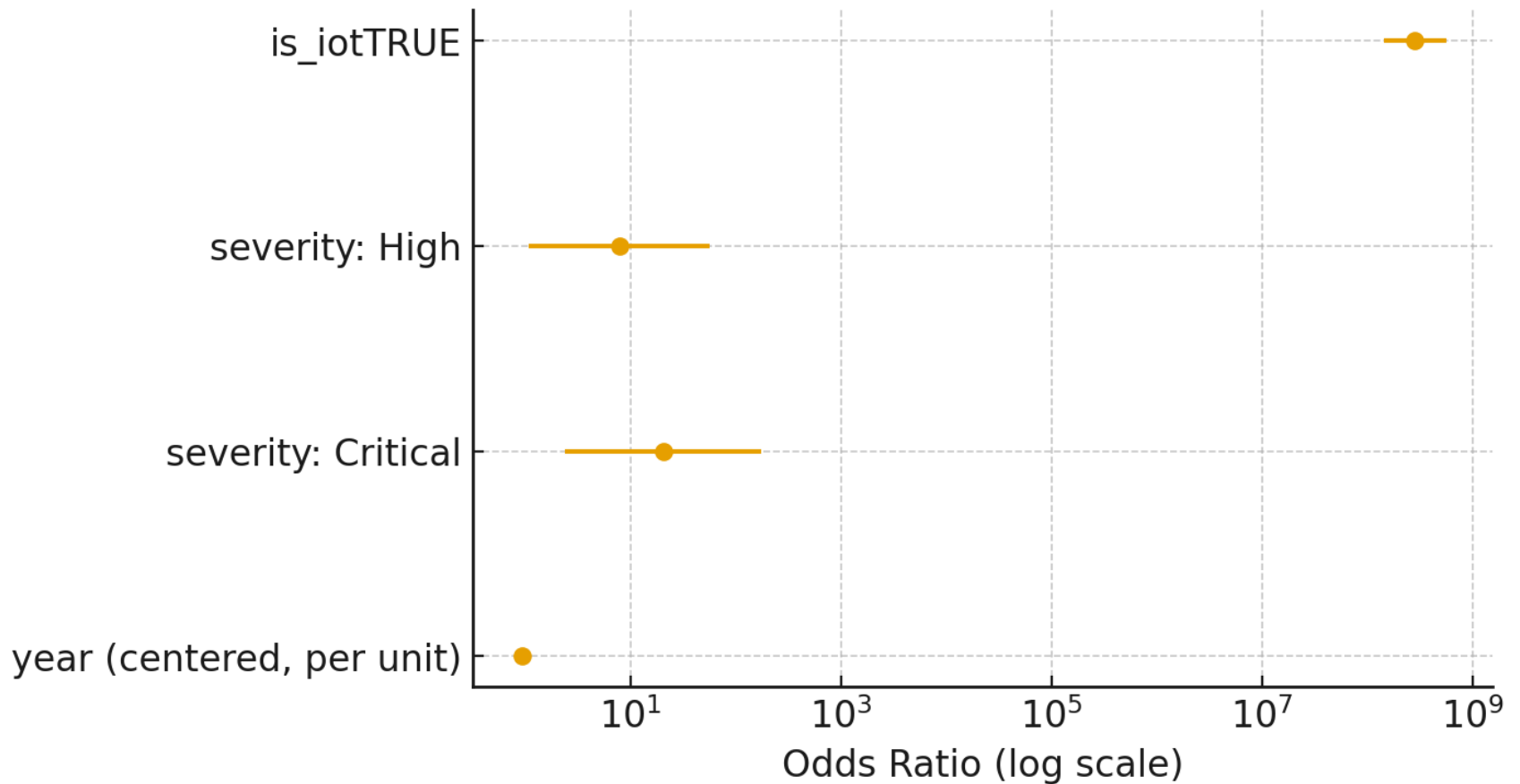


Severity (High): OR  $\approx 7.75$  ( $p = 0.042$ )



Year: OR  $\approx 0.93$  ( $p \approx 0.05$ )

## GLM (Robust) Odds Ratios



# Mixed-Effects (MLM) Results

IoT (TRUE): OR  $\approx 7.5 \times 10^8$  ( $p < 0.001$ )



Severity (Critical): OR  $\approx 19.9$  ( $p = 0.001$ )

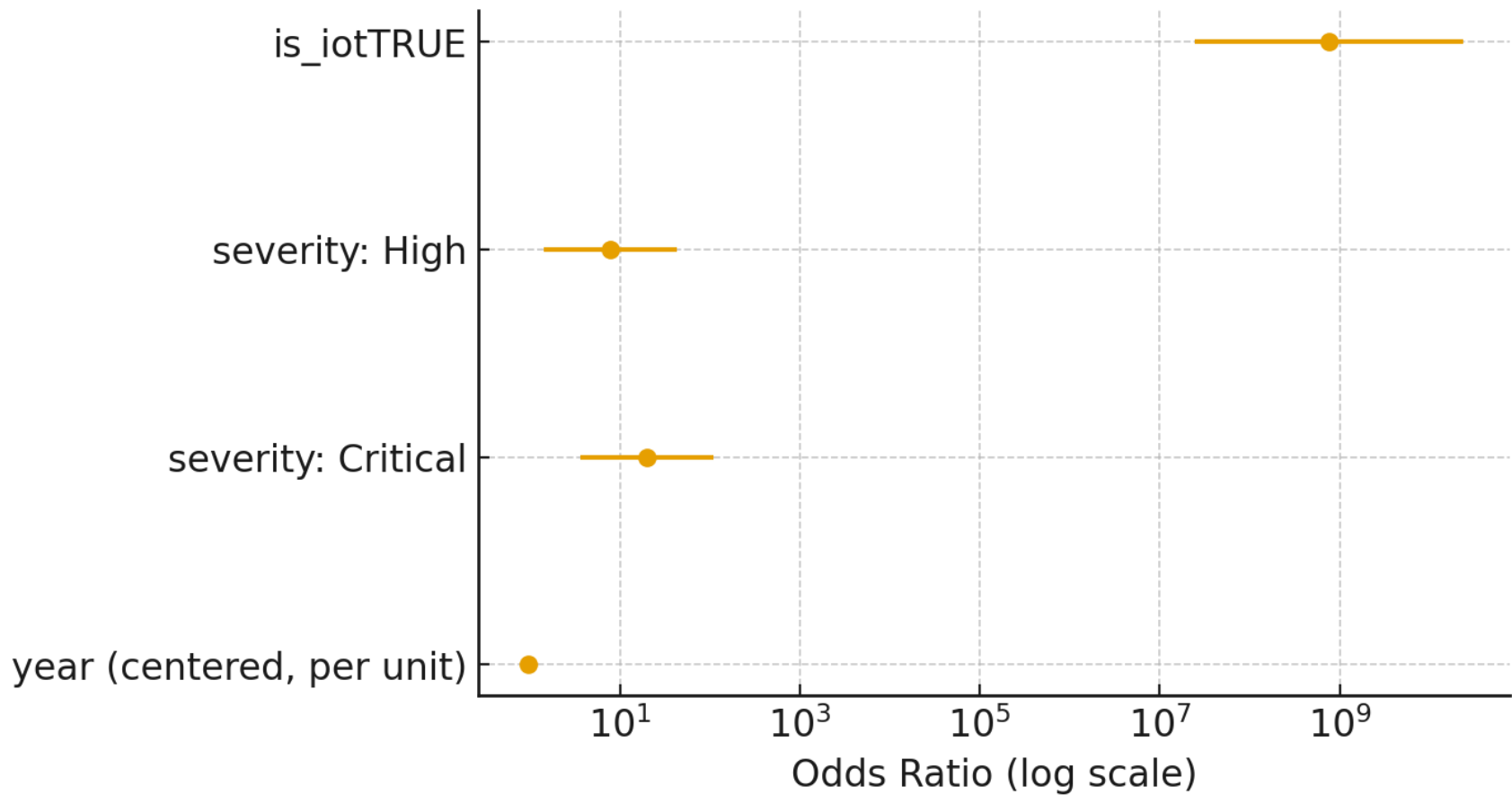


Severity (High): OR  $\approx 7.75$  ( $p = 0.018$ )



Year: OR  $\approx 0.94$  ( $p = 0.077$ )

## MLM Fixed-Effects Odds Ratios



# Key Statistical Findings



IoT CVEs  $\approx$  18% of total



IoT exploitation risk  $\approx 10^8\times$  higher



Severity and IoT both predict exploitability



Slight decline post-2023

Transition:  
Machine  
Learning  
Phase  
(Work in  
Progress)

Next stage will  
apply ML models  
to predict  
exploitability.

Currently in  
progress — model  
training phase.

# Planned Machine Learning Framework

Supervised: SVM, Random Forest, BERT

Unsupervised: K-Means, DBSCAN

Goals:

- Predict exploitability
- Cluster vulnerabilities
- Automate prioritization

# Expected ML Outcomes

- Predict exploitability likelihoods

- Identify emerging zero-day clusters

- Prioritize high-risk IoT CVEs

- Improve patch response times


## Research Impact and Implications

- Enhances IoT risk awareness


- Strengthens vulnerability disclosure practices

- Provides foundation for predictive threat intelligence

Preliminary results confirm IoT vulnerabilities are disproportionately exploited.



Machine learning phase will enhance predictive capabilities.



Thank you — Questions welcome.