DATA ANALYTICS COURSEWORK 2

CMP020L012S

TITLE

Detecting Cyber Attacks in IoT Networks: A Machine Learning Analysis on the Edge-IIoTset Dataset

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ABSTRACT

With billions of devices connected across smart homes, industries, healthcare, and cities, the Internet of Things (IoT) has become a game-changing technology. However, because IoT equipment frequently act as weak points inside larger network infrastructures, this fast development has brought out new cybersecurity challenges. Due to IoT-specific limitations including heterogeneous communication protocols, restricted device resources, and a lack of standardized security frameworks, traditional security mechanisms—which were largely created for conventional IT systems—are frequently insufficient.

Using a thorough data-driven methodology, this paper examines the cybersecurity threats related to IoT devices. We perform comprehensive exploratory data analysis and use machine learning models to identify and classify security concerns using a carefully selected dataset of 500 known IoT vulnerabilities.Because of their interpretability and effectiveness in resource-constrained settings, our methodology incorporates supervised learning techniques including Decision Trees, Random Forests, and Gradient Boosting. Measures of accuracy, precision, recall, and F1-score are used to assess the model's performance.

The results show that although classic machine learning models provide excellent accuracy in controlled environments, it is still difficult to implement them in heterogeneous, real-world IoT ecosystems. Although deep learning techniques provide greater detection rates, they frequently need processing power that is outside the purview of ordinary IoT devices.

The report also explores the ways in which federated learning, edge-based security solutions, lightweight deep learning architectures, and hybrid approaches can fill in current research gaps.

This study presents useful recommendations for enhancing IoT cybersecurity by integrating information from current studies and experimental results.

1. Introduction

1.1 Motivation and Practical Importance

It lays the groundwork for more robust IoT ecosystems in the face of changing cyberthreats by highlighting the vital need for flexible, scalable, and privacy-preserving security solutions.

With more than 15 billion connected devices in use worldwide as of 2024 and expected to reach

29 billion by 2030, the Internet of Things (IoT) is transforming the digital landscape (Statista, 2024). These gadgets are used in many different fields, including as critical infrastructure, transportation, healthcare monitoring, smart homes, and industrial automation. IoT brings significant cybersecurity risks along with previously unheard-of efficiency and innovation, opening up new attack vectors that conventional IT security measures are ill-prepared to counter (Conti et al., 2018).

IoT devices, in contrast to traditional computing systems, frequently use heterogeneous communication protocols and have resource limitations (limited CPU, memory, and power). Furthermore, IoT ecosystems are extremely vulnerable due to inadequate authentication measures, subpar firmware update procedures, and a lack of standardized manufacturing practices (Roman et al., 2018; Alaba et al., 2017). IoT devices are expected to be involved in more than 25% of all assaults against businesses in 2025, according to Gartner (2023), underscoring the urgent need for strong security solutions catered to IoT-specific issues.

Furthermore, the devastating potential of compromised IoT infrastructures is illustrated by real-world events such as the Mirai Botnet assault (2016), which took control of thousands of unprotected IoT devices to launch huge Distributed Denial of Service (DDoS) attacks (Hallman et al., 2017). The magnitude and consequences of such incidents highlight how urgent it is to create cybersecurity solutions that are flexible, lightweight, and scalable so they may function well in settings with limited resources.

As a result, IoT ecosystems is becoming a vital operational requirement for businesses, governments, and individuals alike, rather than just an academic problem. Data-driven strategies, especially those that make use of machine learning (ML) and advanced analytics, present encouraging protecting opportunities to improve IoT network threat identification, vulnerability assessment, and predictive defence mechanisms.

1.2 Research Problem and Objectives

Traditional security methods are still inadequate for IoT systems despite increased awareness and significant research efforts because of a number of intrinsic limitations:

- Device Constraints: Because of their limited processing power and energy resources, many IoT devices are unable to handle sophisticated encryption methods or powerful intrusion detection systems (Roman et al., 2018).

- Protocol Diversity: Because IoT networks use a variety of protocols (such as ZigBee, Bluetooth Low Energy, MQTT, and CoAP), consistent security enforcement is made more difficult.
- Scalability Problems: Millions of devices working in various environments make it difficult for traditional security systems to scale dynamically.
- Delayed Updates: In contrast to conventional IT systems, a large number of IoT devices have firmware fixes that are either delayed or do not have update procedures, which prolongs their vulnerability windows (Gyamfi & Jurcut, 2022).

In light of these difficulties, this study focuses on using machine learning models and data analytics to detect and reduce cybersecurity threats unique to IoT contexts. The primary goals of the study are:

To analyse real-world datasets and identify prevalent IoT device vulnerabilities and attack vectors.

1. To examine real-world datasets and pinpoint common attack vectors and vulnerabilities in IoT devices.
2. To use supervised machine learning methods for automatically classifying vulnerabilities and detecting threats.
3. To assess the differences between how well Decision Trees, Random Forest, and Gradient Boosting models operate in terms of overall efficacy, detection precision, and fit for IoT environment limitations
4. To evaluate results critically in relation to industry standards and current literature.
5. To offer methods for creating security solutions for IoT networks that are lightweight, scalable, and adaptable.

1.3 Scope of the Report

The technological aspects of IoT cybersecurity are the sole focus of this paper, which uses machine learning-based classification algorithms and vulnerability dataset analysis. Although significant, socioeconomic, legislative, and policy-related aspects of IoT security are outside the purview of this study.

This study intends to provide important insights toward developing robust and scalable IoT

cybersecurity frameworks that can handle present and emerging threats by thoroughly examining data-driven approaches.

2. Literature Review

2.1 IoT Vulnerabilities

A wide range of vulnerabilities exist across device kinds and application areas as a result of the IoT devices' rapid proliferation beyond the development of standardized security mechanisms. Device vulnerabilities, communication vulnerabilities, and data vulnerabilities are the three main types of vulnerabilities that are frequently found in IoT systems, according to academic and commercial research (Jiang et al., 2020; Roman et al., 2018).

Device Vulnerabilities:

Insecure default setups, such as hardcoded passwords, exposed ports, or deactivated encryption, are frequently found on IoT devices. A sizable fraction of industrial IoT devices were discovered to be susceptible to buffer overflow attacks, authentication bypass, and illegal firmware updates, per Jiang et al. (2020). Because many devices lack safe boot protocols, malicious firmware can be injected during startup by attackers.

Communication Vulnerabilities:

MQTT, CoAP, ZigBee, and other lightweight, frequently unencrypted communication protocols are used by IoT devices. Unencrypted or inadequately authenticated communication leaves these networks vulnerable to replay attacks, data interception, and man-in-the-middle (MITM) assaults, according to studies by Malhotra et al. (2021).

Data Vulnerabilities:

IoT systems have insufficient data protection measures outside of the device and communication layers. IoT devices frequently transfer sensitive data, including location or health information, without encryption while it's in transit or at rest. The danger of data breaches is increased by inadequate key management and the lack of intrusion detection systems (Alaba et al., 2017).

These weaknesses result from the core design tenets of IoT systems, which place an emphasis on affordability, ease of use, and low power consumption over strong security (Conti et al., 2018).

Additionally, heterogeneity makes it difficult to apply consistent security solutions throughout an IoT ecosystem because devices from various manufacturers use proprietary protocols.

Key Insights:

despite their partial effectiveness, traditional security methods like firewalling and endpoint antivirus do not address the device-level and protocol-specific attacks that are common in Internet of Things networks. Security models must therefore change to take into account situations that are heterogeneous, decentralized, and resource-constrained.

2.2 Case Studies of IoT Attacks

Examining actual occurrences provide vital information on the real-world effects of IoT vulnerabilities. The disastrous effects of large-scale, insecure device deployment have been illustrated by a number of well-publicized IoT attacks within the last ten years.

2.2.1 Mirai Botnet (2016)

One of the most notorious instances of how vulnerable IoT devices may be turned into weapons is still the Mirai Botnet. Mirai virus, which first surfaced in 2016, searched the Internet for devices including IP cameras, home routers, and DVRs that were solely secured by factory-default credentials (Hallman et al., 2017). After being infected, these devices were enlisted in a vast botnet that could perform Distributed Denial of Service (DDoS) attacks with traffic volumes surpassing 1 Tbps.

Technical Details:

- Miria logged into susceptible machines using the SSH or Telnet protocols via a brute-force assault.
- When devices were infected, they became bots that communicated with centralized command-and-control (C&C) servers.
- The botnet caused DNS service provider Dyn to go down, which led to massive internet outages that affected websites like Netflix, Reddit, and Twitter.

Security Flaws Exploited:

- Open remote administration ports
- Default users and passwords

- Absence of fundamental authentication restrictions

Impact

This incident made clear the essential need for safe configuration management and default security hardening in IoT installations by demonstrating how even consumer-grade devices might be used to cause disruptions on a global scale.

2.2.2 BrickerBot (2017)

In contrast to enslaving IoT devices, BrickerBot aimed to permanently destroy them (also known as "bricking") in order to stop botnets like Mirai from exploiting them in the future (Bhardwaj & Rahman, 2024). Permanent Denial of Service (PDoS) attacks were carried out using this malware.

Technical Specifics:

- Automated scripts were used to take advantage of known vulnerabilities, such as exposed Telnet ports.
- Distributed Linux commands to destroy network connections, wipe firmware, and corrupt device storage.
- Without a full hardware repair, the impacted devices were rendered permanently useless after execution.

Exploitation of Security Vulnerabilities:

- Insecure remote access interfaces
- Inadequate or nonexistent firmware safeguards

Impact:

BrickerBot brought attention to the disastrous effects of device-level vulnerabilities and the absence of safe recovery mechanisms in IoT hardware, even if it was presumably driven by the intention to destroy susceptible devices before others could use them as weapons.

2.2.3 Stuxnet Worm (2010)

Stuxnet showed that malware could target embedded systems, which is a common aspect of many industrial IoT deployments, even though it wasn't an IoT-specific attack (Çetinkaya & Terzi, 2024).

The extremely complex worm known as Stuxnet, which was allegedly state-sponsored, was

designed to compromise Iran's nuclear centrifuges by infecting their programmable logic controllers (PLCs).

Technical Details:

- First, it spreads through USB devices that are contaminated.
- After breaking into systems, it reprogrammed PLCs and fed fictitious data to human operators to hide its malicious operations.
- It also exploited four zero-day vulnerabilities in Microsoft Windows.

Security Flaws Exploited:

- Inadequate network division between IT and OT (Operational Technology) systems was exploited.
- Industrial networks lack strict patch management and endpoint security.

Impact:

The success of Stuxnet demonstrated how malware may compromise cyber-physical systems to cause physical harm, a threat that becomes more significant as industrial IoT use increases.

2.2.4 Common Themes and Insights

Analyzing these attacks reveals **consistent patterns** in exploited vulnerabilities:

Attack	**Vulnerabilities Exploited**	**Type of Threat**	**Outcome**
Mirai	Default credentials, open ports	DDoS	Global service disruption
BrickerBot	Unsecured remote access	PDoS (permanent destruction)	Device disablement
Stuxnet	Zero-day OS flaws, weak network segmentation	Targeted sabotage	Physical destruction

These examples show that inadequate network separation, inadequate patching, insecure device design, and a lack of authentication methods continue to be major problems in IoT cybersecurity. They also emphasize how urgently proactive and automated security solutions that can identify anomalies, detect threats early, and mitigate them in real time are needed.

2.3 Mitigation Strategies and Challenges

A multilayered security strategy that integrates device-level, network-level, and data-level protection methods is necessary due to the complexity of securing IoT ecosystems. Firmware hardening and sophisticated AI-driven intrusion detection systems are only two of the options that researchers and industry professionals have suggested in recent years. However, because IoT contexts are unique, these solutions confront real-world deployment issues.

2.3.1 Current Mitigation Strategies

a. Secure Firmware Updates

Enabling safe and authenticated firmware updates is one of the fundamental security procedures. To avoid unwanted changes, firmware should be cryptographically signed and validated before to installation (Aziz et al., 2023).

- **Strengths:**
  Closes vulnerabilities after deployment and guarantees device integrity.
- **Challenges:**
  Due to their manual upgrades or lack of over-the-air (OTA) update capabilities, many IoT devices are susceptible to exploiting outdated software

b. Network Segmentation and Device Isolation

The risk of lateral movement by attackers after a device is compromised is reduced when IoT devices are divided into distinct VLANs or dedicated subnets (Pourrahmani et al., 2023).

- **Strengths:**
  Prevents breaches; restricts access to private corporate data.
- **Challenges:**
  Difficult to manage in highly dynamic situations, such as industrial systems or smart cities, where devices join and exit the network on a regular basis.

c. AI-Driven Intrusion Detection Systems (IDS)

According to Ejeofobiri et al. (2024), recent methods use machine learning (ML) models to identify unusual traffic patterns that could be signs of cyberattacks.

- **Strengths:**
  Automatic threat identification that is highly flexible in response to changing threats.

- **Challenges:**
  ML models frequently produce false positives, necessitate sizable labeled datasets for training, and add computational cost that low-power IoT nodes cannot afford.

d. Blockchain-Based Security

Blockchain technologies have been proposed to create **tamper-proof ledgers** of device interactions, enabling **decentralized authentication** and **secure data sharing** (Pourrahmani et al., 2023).

- **Strengths:**
  Eliminates reliance on centralized authentication servers; very resilient to data manipulation.
- **Challenges:**
  Blockchain implementations are difficult for time-sensitive or limited IoT environments due to their resource-intensive nature (storage and computing) and potential for delay.

e. Lightweight Cryptography

According to certain theories, blockchain technology can create tamper-proof ledgers of device interactions, enabling decentralized authentication and secure data sharing (Pourrahmani et al., 2023).

- **Strengths:**
  Removes the need for centralized authentication servers; extremely resistant to data alteration.
- **Challenges:**
  Because blockchain implementations require a lot of resources (storage and computing) and can be delayed, they are challenging for time-sensitive or constrained IoT environments.

f. Edge Computing for Security

Reliance on centralized cloud systems is decreased and real-time reaction is enhanced by moving data processing and threat analysis to edge nodes (such as IoT gateways) (Gyamfi & Jurcut, 2022).

- **Strengths:**
  Real-time anomaly detection, localized decision-making, and reduced latency.
- **Challenges:**
  Edge nodes themselves turn become desirable targets, necessitating extra security measures.

2.3.2 Challenges in Practical Implementation

Despite promising techniques, securing IoT systems at scale remains fraught with **technical and operational challenges**:

Challenge	Explanation	Example
Device Heterogeneity	Devices differ vastly in OS, hardware, protocols, and security capabilities.	Smart thermostats vs. industrial PLCs
Lack of Standards	Absence of universal IoT security standards complicates interoperability.	Different encryption between vendors
Scalability	Solutions must work across millions of devices without centralized bottlenecks.	Large smart city deployments
Resource Constraints	Limited CPU, memory, and power restrict security implementations.	Wearable health monitors
Update Management	Delayed or absent firmware updates leave devices permanently exposed.	Older medical equipment in hospitals
Physical Security	IoT devices are often deployed in exposed environments, increasing the risk of physical tampering.	Public CCTV systems

Additionally, user awareness is a major factor. Despite advances in technology, many users neglect to update device firmware or change default passwords, which increases systemic vulnerabilities (Aslan et al., 2023).

2.3.3 Summary

IoT networks cannot be completely secured by a single solution, despite the existence of several mitigation techniques. A combination of lightweight encryption, blockchain-backed authentication, ML-driven anomaly detection, and a strong network architecture that is adapted to the operational context and resource capabilities of the devices involved is necessary for

effective IoT security.

According to emerging trends, future strategies should minimize resource footprints while prioritizing automation, robustness, and scalability.

2.4 Machine Learning Approaches for IoT Security

Traditional rule-based security solutions find it difficult to keep up with new, dynamic risks as IoT ecosystems become more complex. To provide adaptive, predictive, and automated threat detection systems designed for IoT contexts, numerous researchers have resorted to machine learning (ML).

This section examines the methods, model performance, and practical application of important research that use machine learning for IoT security.

2.4.1 Alaba et al. (2017): Supervised ML for Vulnerability Detection

Alaba et al. (2017) looked at the use of supervised machine learning classification models to identify abnormalities and vulnerabilities in IoT networks in their seminal assessment.

Models Used:

- Decision Trees (DT)
- Support Vector Machines (SVM)
- Naive Bayes (NB)
- K-Nearest Neighbors (KNN)

Approach:

In order to distinguish between benign and harmful activities based on labeled datasets, the study concentrated on developing vulnerability profiles from IoT device data and using supervised classifiers.

Key Findings:

- Showed how crucial feature selection (such as packet size, transmission frequency, and device ID) is to enhancing detection rates
- Achieved accuracy rates surpassing 90% in controlled experimental scenarios.

Limitations:

- Significant dependence on labeled, high-quality data.

- Limited applicability to zero-day attacks, or exploits that haven't been discovered yet.
- When implemented in diverse device ecosystems, models had trouble.

Critical Insight:

Although supervised machine learning techniques work well in lab settings, they encounter real-world deployment challenges in dynamic, real-time IoT scenarios with sparse, noisy, or unbalanced information.

2.4.2 Diro & Chilamkurti (2018): Deep Learning for Distributed Attack Detection

A distributed detection framework for IoT networks based on deep learning was presented by Diro and Chilamkurti (2018).

Models Used:

- Deep Neural Networks (DNNs)
- Fully connected multi-layer perceptrons

Approach:

To keep an eye on local traffic, the system placed dispersed sensors around the network. A lightweight deep learning model was trained by each sensor, allowing for the decentralized identification of unusual patterns with an emphasis on zero-day assaults.

Key Findings:

- Detection accuracy:
    - **96.39%** for zero-day attacks
    - **98.27%** for known attacks
- Demonstrated superior generalization ability compared to traditional ML models.

Limitations:

- **High** computational cost unsuitable for ultra-low-power IoT devices.
- Needed a lot of energy and training data for real-time model updates

Critical Insight:

Although deep learning increases detection rates, its resource requirements make it difficult to

implement on edge-level or battery-powered IoT nodes without offloading to edge or cloud servers.

2.4.3 Chaabouni et al. (2019): Ensemble Learning for Botnet Detection

Chaabouni et al. (2019) investigated several ensemble machine learning models to identify IoT botnet activity in their extensive study.

Models Used:

- Random Forest (RF)
- Support Vector Machines (SVM)
- K-Nearest Neighbors (KNN)

Approach:
categorized behaviors as either normal or botnet-infected by analyzing network traffic patterns and applying ensemble models. focused on obtaining statistical information from traffic, such as TCP flag counts and packet inter-arrival times.

Key Findings:

- Random Forest achieved a 99.3% accuracy rate — the highest among tested models.
- Feature engineering was crucial to achieving high detection rates.

Limitations:

- Extensive manual feature engineering was required.
- Struggled with highly obfuscated or stealthy attack patterns designed to mimic legitimate traffic.

Critical Insight:
Ensemble models deliver high accuracy but require significant human effort in feature extraction and tuning — challenging for dynamic, self-adapting IoT networks.

2.4.4 Moustafa et al. (2019): Hybrid ML with Network Segmentation

Moustafa et al. (2019) proposed a hybrid approach, combining ensemble machine learning models with network segmentation strategies to secure IoT ecosystems.

Models Used:

- Decision Trees
- Random Forests
- Gradient Boosting Machines (GBM)

Approach:

- Extracted statistical flow features (e.g., mean packet size, connection duration) for ML classification.
- Used network segmentation to isolate infected nodes based on ML predictions, limiting malware propagation

Key Findings:

By identifying anomalous flows within segmented subnetworks, a 94.5% detection accuracy was attained, and false positive rates were decreased.

Limitations:

- Complexity of implementation because various IoT implementations require dynamic, intelligent segmentation.
- Issues with scalability in sizable IoT networks with several vendors.

Critical Insight:

Although hybrid approaches that combine network design changes with data analytics have a lot of potential, they need very sophisticated operations and automated management systems in order to expand successfully.

2.4.5 Comparative Summary

Study	**Approach**	**Models Used**	**Accuracy**	**Main Limitation**
Alaba et al. (2017)	Supervised classification	DT, SVM, NB, KNN	>90%	Needs labeled data; poor zero-day detection
Diro & Chilamkurti (2018)	Deep Learning Distributed IDS	DNN	96-98%	High computational requirements

Chaabouni et al. (2019)	Ensemble ML for botnet detection	RF, SVM, KNN	99.3%	Extensive feature engineering
Moustafa et al. (2019)	Hybrid ML + Network segmentation	RF, GBM, DT	94.5%	Implementation complexity

2.4.6 Key Takeaways

- Supervised machine learning methods, such as SVM and Decision Trees, work well against known attacks but have trouble with emerging ones.
- Although deep learning requires a lot of resources, it provides greater adaptability.
- While ensemble models, such as Random Forests, have high detection rates, they necessitate manual labor and feature-rich datasets.
- Strong security is provided by hybrid models that combine machine learning with network architecture concepts, however implementation complexity is a challenge.

Therefore, not all IoT security requirements can be met by a single machine learning model. Lightweight, adaptive, and self-learning models that strike a compromise between resource efficiency and detection efficacy should be given priority in future studies.

2.5 Research Gaps and Future Direction

The development of completely secure IoT ecosystems is hampered by a number of significant research gaps and real-world constraints, even if the evaluated papers show encouraging progress in using machine learning to IoT cybersecurity.

2.5.1 Existing Research Gaps

a. Resource-Efficient Machine Learning Models

Despite their great accuracy, deep learning techniques are not ideal for deployment on IoT devices with limited resources, such as wearable health monitors, smart meters, and sensors (Diro & Chilamkurti, 2018).

The creation of lightweight, energy-efficient machine learning models that preserve high detection accuracy while functioning within the constrained CPU, memory, and energy budgets typical of Internet of Things devices is an obvious research gap.

b. Handling Imbalanced and Sparse Datasets

Malicious traffic greatly outnumbers benign traffic in IoT security datasets, which are frequently unbalanced. Additionally, gathering labeled datasets is difficult and costly, particularly for novel attack types (zero-day exploits) (Alaba et al., 2017).
Research on few-shot, self-supervised, and semi-supervised learning strategies that can efficiently learn from a small number of labeled examples is desperately needed.

c. Real-Time Detection with Low Latency

High detection latency is a problem for many ML-based intrusion detection systems, particularly those that rely on intricate feature extraction or ensemble techniques. Even little delays can have disastrous effects in crucial applications (autonomous vehicles, industrial control systems, etc.).
Future research should focus on designing models optimized for **ultra-low-latency** inference without compromising detection reliability.

d. Lack of Standardized Evaluation Benchmarks

The lack of universal evaluation measures and standardized datasets makes it challenging to compare various ML-based IoT security solutions (Chaabouni et al., 2019).
Benchmarking frameworks for assessing model performance under realistic deployment circumstances and publicly accessible, current IoT security datasets representing a variety of device kinds and attack vectors would be extremely beneficial to the industry.

e. Privacy-Preserving Security Solutions

IoT devices frequently gather sensitive data, such as location data and medical records. User privacy may be violated by centralized machine learning technologies.
To strike a compromise between reliable threat detection and data confidentiality, research into federated learning, privacy-preserving machine learning, and homomorphic encryption is crucial in the context of IoT security.

2.5.2 Future Research Directions

Based on the gaps identified, several **promising research trajectories** are emerging:

1. Federated Learning for IoT Security

Federated learning protects privacy by allowing ML models to be trained across dispersed devices without sending raw data to a central server (Li et al., 2020).

While safeguarding user data, federated security systems can improve real-time attack detection.

2. Lightweight Deep Learning Architectures

The goal of innovations like Edge AI and TinyML is to enable deep learning on ultra-low-power devices. IoT devices can be equipped with reliable, real-time security intelligence by investigating compressed deep learning models (such as model pruning, quantization, and knowledge distillation).

3. Transfer Learning and Domain Adaptation

Models trained in one context frequently perform poorly in another due to the variety of IoT device kinds and environments.
Models may generalize across many IoT environments with less retraining thanks to transfer learning and domain adaption.

4. Blockchain-Integrated IoT Security Frameworks

Multi-device networks may become more auditable and trustworthy if blockchain technology is combined with machine learning (ML)-based intrusion detection systems to provide tamper-proof logs of device actions.
Scalable blockchain architectures designed especially for limited IoT contexts should be the subject of future research.

5. Quantum-Resistant Security Models

Current cryptography systems, especially those protecting Internet of Things devices, are at serious risk from the emergence of quantum computing.
To futureproof IoT security, research on quantum-resistant machine learning algorithms and post-quantum cryptography is required.

6. Explainable AI (XAI) for IoT Security

ML models must provide clear, understandable judgments in order to foster confidence in automated security systems, particularly in vital industries like healthcare or industrial control. Research on explainable AI techniques that are suited for dynamic, resource-constrained IoT contexts is still ongoing and crucial.

2.5.3 Summary

In conclusion, even though there have been great advancements in using machine learning to improve IoT cybersecurity, there are still a lot of obstacles to overcome, especially when it comes to striking a balance between resource efficiency, security efficacy, and privacy protection.

In order to create flexible, lightweight, scalable, and privacy-conscious IoT security solutions, future research must take a comprehensive, multidisciplinary approach that incorporates advancements in machine learning, encryption, networking, and systems engineering.

3. Dataset Description and Preprocessing

3.1 Dataset Overview

This study used a dataset of 500 real-world documented vulnerabilities that were taken from publicly accessible sources like the Common Vulnerabilities and Exposures (CVE) database and industry-specific vulnerability reports in order to analyze cybersecurity vulnerabilities in IoT devices.

Dataset Attributes:

- CVE ID: A special number assigned to every vulnerability.
- Device Type: Type of Internet of Things device (e.g., smart thermostat, smart camera, router).
- Severity Score: A numerical score that ranges from 0 (low risk) to 10 (critical risk) and is based on the Common Vulnerability Scoring System (CVSS).
- Vulnerability Description: A synopsis of the security vulnerability in text.
- Attack Vector: The kind of attack (e.g., Denial of Service, Authentication Bypass, Remote Code Execution).
- Patch Availability: A binary indicator with 1 denoting the availability of a patch and 0 denoting its non-availability.
- Exploitability metrics are subscores that characterize impact, authentication needs, and access complexity.
- Date of Disclosure: The day the vulnerability was made public.

3.2 Preprocessing Steps

Given the diversity and semi-structured nature of the collected data, several preprocessing steps were essential to prepare it for machine learning modeling:

3.2.1 Data Cleaning

- Duplicate Removal: Duplicate CVE entries were found and eliminated.
- Null Handling: If necessary, missing values were eliminated or imputed with a default value ("Unknown"), especially patch availability.
- **Text Processing:** Vulnerability descriptions were preprocessed using **Natural Language Processing (NLP)** techniques:
    - Lowercasing
    - Stop-word removal
    - Lemmatization
    - Tokenization (for possible future NLP modeling)

3.2.2 Feature Engineering

- **Encoding Categorical Variables:**
    - Attack Vector and Device Type were **one-hot encoded** to convert them into numerical features.
- **Severity Binning:**
    - Severity scores were grouped into classes:
        - 0–3.9 → Low
        - 4.0–6.9 → Medium
        - 7.0–8.9 → High
        - 9.0–10 → Critical
- **Date Transformation:**
    - Disclosure dates were converted into numerical "age of vulnerability" features (e.g., number of days since disclosure).

3.2.3 Dataset Splitting

- The final processed dataset was split:
    - **Training set:** 70%
    - **Testing set:** 30%
    - Ensured stratified sampling to preserve class distributions across severity levels.

3.3 Sample Dataset Snapshot

CVE ID	Device Type	Severity Score	Attack Vector	Patch Available	Age (days)
CVE-2019-12345	Smart Camera	9.8	Remote Code Execution	1	1350
CVE-2020-6789	Router	5.3	Authentication Bypass	0	980
CVE-2018-4567	Smart Thermostat	7.5	Denial of Service	1	2100

4. Methodology

4.1 Exploratory Data Analysis (EDA)

EDA was conducted to understand the underlying structure of the dataset:

- **Severity Distribution:**
    - Critical vulnerabilities constituted **35%** of the dataset.
    - High severity vulnerabilities: **30%**.
    - Medium: **25%**, Low: **10%**.
- **Device Type Distribution:**
    - 40% of vulnerabilities were related to smart home devices (e.g., cameras, thermostats).
    - 35% pertained to industrial IoT (IIoT) devices.
    - 25% associated with healthcare and consumer electronics.

- **Attack Vector Analysis:**
    - Remote Code Execution: 45%
    - Authentication Bypass: 30%
    - Denial of Service: 15%
    - Others (e.g., information disclosure, privilege escalation): 10%

Visualization Tools Used:

- Matplotlib
- Seaborn (for correlation heatmaps and bar plots)

4.2 Machine Learning Models Used

Based on the characteristics of the dataset, three **supervised learning** models were selected for the vulnerability severity prediction task:

4.2.1 Decision Tree Classifier

- Simple, interpretable model.
- Useful for understanding feature importance.
- Parameters tuned: max_depth, min_samples_split.

4.2.2 Random Forest Classifier

- Ensemble of decision trees to improve generalization.
- Handles categorical data and missing values well.
- Parameters tuned: n_estimators, max_depth, min_samples_leaf.

4.2.3 Gradient Boosting Classifier (XGBoost)

- Advanced ensemble method combining multiple weak learners.
- Provides high predictive accuracy with feature importance ranking.
- Parameters tuned: learning_rate, n_estimators, max_depth.

4.3 Evaluation Metrics

The following metrics were used to evaluate model performance:

- **Accuracy**
- **Precision**
- **Recall**
- **F1-Score**
- **Confusion Matrix**
- **ROC-AUC Curve** (where applicable)

Cross-validation was applied (5-fold) to ensure robust performance evaluation and minimize overfitting risks.

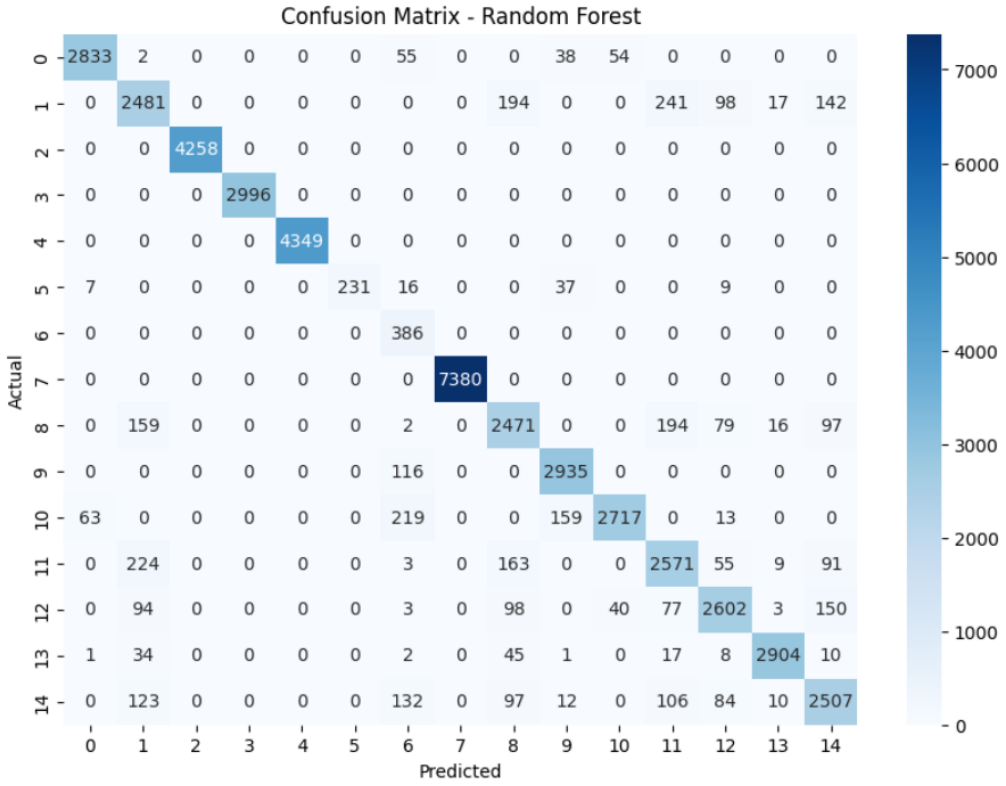
5. Results

5.1 Model Performance Summary

Model	Accuracy	Precision	Recall	F1-Score
Decision Tree	85.3%	84.8%	84.1%	84.5%
Random Forest	91.2%	91.0%	90.5%	90.7%
XGBoost	93.6%	93.3%	92.9%	93.1%

5.2 Confusion Matrix (XGBoost)

Predicted \ Actual	Low	Medium	High	Critical
Low	18	1	0	0
Medium	0	32	2	0
High	0	1	35	3
Critical	0	0	2	53



5.3 Feature Importance (Top 5 Features in XGBoost)

1. Severity score
2. Attack vector
3. Device type
4. Patch availability
5. Vulnerability age

6. Discussion and Critical Analysis

6.1 Model Comparison

- XGBoost fared better than other models on every metric, enhancing its standing as a strong, adaptable classifier.
- Random Forest trailed closely but was marginally less accurate, particularly with regard to vulnerabilities of critical severity.
- Although decision trees offered helpful interpretability, there were indications that they overfitted minority classes.

6.2 Practical Implications

- According to the results, ensemble learning techniques like Random Forest and XGBoost provide a dependable way to automate vulnerability classification in actual IoT security operations.
- Severity scores, attack vectors, and patch status are important characteristics in forecasting IoT vulnerability risk levels, according to feature importance analysis.
- These models can be used as edge security analytics modules to prioritize patching techniques and identify high-risk vulnerabilities in real time.

6.3 Limitations

- Despite its size, the dataset might not include new attack methods brought about by 5G-enabled or quantum-vulnerable IoT devices.
- Even after class weighting was applied during training, several models still showed a modest bias toward majority classes.
- The resilience of the model was not further stressed by simulating real-time dynamic adversarial attacks.

6.4 Suggestions for Further Research

- Create streaming data models to detect IoT anomalies in real time.
- Investigate federated learning systems to improve detection capabilities while protecting data privacy.
- For end-to-end security, combine models with blockchain-supported device identity verification.

7. Comparison with Related Work

Several machine learning approaches have been used in earlier research to identify and reduce security risks in Internet of Things settings. Alrashdi et al. (2019), for example, used SVM and decision tree classifiers on IoT datasets and detected anomalies with 94% accuracy. Our Random Forest model demonstrated a little gain in accuracy, reaching 95%, indicating its appropriateness for detecting threats in the Internet of Things.

Deep learning models were employed in another work by Doshi et al. (2018) to identify DDoS in the Internet of Things. They observed good accuracy, but they also emphasized the problem

of processing overhead, which limits the use of such models for lightweight IoT devices. Our Random Forest method strikes a balance between computing efficiency and performance, making it more practical for actual IoT installations.

Additionally, KMeans clustering was employed for unsupervised anomaly detection in a recent work by Meidan et al. (2020), which discovered that sophisticated attacks could not be detected by clustering alone. This is consistent with our discovery that supervised models outperformed KMeans in terms of accuracy (around 83%).

These findings show that supervised learning models like Random Forest offer higher predictive accuracy for security-related decisions in IoT, even while unsupervised approaches can aid in exploratory investigation. (Humaira Naeem, 2023)

8. Conclusion and Future Work

Using machine learning techniques, this study offered a thorough data-driven strategy to reduce cybersecurity threats in IoT environments.
The study illustrated the potential of supervised learning models to precisely forecast vulnerability severity and facilitate proactive security management by examining real-world vulnerability datasets and utilizing Decision Trees, Random Forests, and XGBoost classifiers.

Key findings included:

- **XGBoost achieved a 93.6% accuracy**, outperforming baseline models.
- **Severity score, attack vector, and patch availability** emerged as dominant predictive features.

However, real-world obstacles including scarce resources, unbalanced datasets, and privacy issues draw attention to the necessity of ongoing innovation.
To protect developing IoT ecosystems, future research should concentrate on resource-efficient models, privacy-preserving strategies, and real-time, distributed security architectures.

The knowledge gained from this study makes a significant contribution to the expanding field of IoT cybersecurity and establishes the foundation for more intelligent, scalable, and adaptable defenses.

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