

Ministry of Higher Education  
and Scientific Research  
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University of Carthage  
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National Institute of Applied  
Sciences and Technology



المعهد الوطني للعلوم التطبيقية و التكنولوجيا  
Institut National des Sciences  
Appliquées et de Technologie

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## Internship Report

### 4th Year of Computer Networks and Telecommunications Engineering

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Subject:

AI-Driven Vulnerability Detection in Smart City  
Prototypes.

host university:



**MANIPAL INSTITUTE  
OF TECHNOLOGY**  
MANIPAL  
*A Constituent Institution of Manipal University*

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*School year :*  
**2023/2024**

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Responsible for the company	Opinion of the internship commission



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Lastly, I wish to express my deep appreciation to IAESTE Tunisia for facilitating this internship opportunity, and to IAESTE LC Manipal India for their warm hospitality and support throughout my stay in India.

# Abstract

The increasing reliance on interconnected devices in smart cities has amplified the potential for cyber-attacks, making cybersecurity a critical concern.

This project focuses on the application of artificial intelligence (AI) to detect vulnerabilities in a smart city prototype. By leveraging machine learning and deep learning algorithms, we aim to predict which devices within the network are most susceptible to hacking.

The project involves analyzing data from smart city environments to identify patterns and indicators of device vulnerabilities. The AI model developed provides a proactive approach to cybersecurity, enabling administrators to address potential threats before they are exploited.

The system is designed to improve the resilience of smart cities by enhancing their ability to detect and respond to cyber risks in real time. Ultimately, this project contributes to the broader goal of creating more secure and resilient smart city infrastructures

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# 1 General Introduction

The rapid development of smart cities has revolutionized urban living, offering enhanced services and a better quality of life through the integration of connected devices and advanced technologies. However, the rise of the Internet of Things (IoT) within these smart infrastructures has introduced significant cybersecurity challenges. As the number of interconnected devices grows, so does the potential for cyber-attacks, making the security of smart city environments a critical concern.

This report focuses on addressing these vulnerabilities by leveraging artificial intelligence (AI) to predict which devices in a smart city prototype are most susceptible to cyber-attacks. AI offers a proactive approach to cybersecurity by analyzing patterns in device behavior and identifying potential vulnerabilities before they can be exploited.

The primary objective of this project is to develop and implement a system capable of assessing the risk associated with each device in the network. Driven by AI models, this system allows city administrators and security teams to detect, monitor, and mitigate cyber risks in real time, ultimately contributing to the creation of safer and more resilient smart city infrastructures.

Throughout this internship at Manipal Institute of Technology, I gained invaluable hands-on experience tackling real-world cybersecurity challenges in smart city environments. The project employed advanced machine learning techniques to build a robust system for vulnerability detection, addressing a pressing issue in the age of IoT.

This report is structured to provide a comprehensive overview of the cybersecurity challenges in smart cities, the methodology used for training AI models for vulnerability detection, and the outcomes of the system's implementation. The successful application of AI in this context demonstrates the potential of machine learning to enhance the security and reliability of smart city networks, addressing a crucial need in modern urban management.

## 2 Presentation of the Host Institution: Manipal Institute of Technology

### 2.1 Overview of Manipal Institute of Technology

Manipal Institute of Technology (MIT), part of Manipal Academy of Higher Education (MAHE) in India, is a prestigious engineering college known for its excellence in research and education in science, technology, and engineering fields. Established in 1957, MIT has grown to offer a variety of undergraduate, postgraduate, and doctoral programs, attracting students from across the world. The institution is committed to fostering a culture of academic rigor, innovation, and hands-on learning. [1]



Figure 1: Logo MIT

### 2.2 Sector of Activities

MIT operates in several sectors, focusing on research, development, and education in engineering and technology:

- **Engineering and Technology Education:** Offering programs in fields like Computer Science, Mechanical Engineering, Electrical Engineering, and Biotechnology, MIT emphasizes both theoretical and practical knowledge.
- **Research and Innovation:** MIT conducts significant research in various areas including Artificial Intelligence (AI), Cybersecurity, Biomedical Engineering, and Robotics, with research centers dedicated to advancing knowledge in these fields.
- **Industry Collaboration:** Through partnerships with national and international organizations, MIT provides students and faculty with opportunities for industrial exposure and collaboration on cutting-edge projects.

## 2.3 Certifications and Accreditations





MIT holds various certifications and accreditations that underscore its commitment to quality education and standards:

- **National Board of Accreditation (NBA):** Accredited by the NBA for several engineering programs, ensuring that the curriculum meets industry and academic standards.
- **NAAC Accreditation:** MIT has received a high rating from the National Assessment and Accreditation Council (NAAC), reflecting its excellence in teaching, infrastructure, and research capabilities.
- **ISO Certification:** The institution adheres to ISO standards for quality management in education, ensuring continuous improvement in academic and administrative processes.

## 2.4 Achievements and Recognition

MIT has achieved numerous accolades in education and research, establishing its reputation as a leading institution:

- **Rankings:** Consistently ranked among the top engineering colleges in India, MIT is recognized for its high standards in education, faculty, and infrastructure.

MIT Ranking					
Agency	2017	2018	2019	2020	2021
	43	39	43	45	<b>51</b>
	15	15	20	21	<b>11</b>
	41	39	28	4*	<b>4*</b>
	4	5	6	5	<b>#</b>

\* Top Private Engineering colleges

# Ranking changed based on discipline (All India Level)

B Tech / BE ( Comp Science)	7
B Tech / BE ( Data Science)	3

Figure 2: MIT Ranking

- **Research Contributions:** MIT has contributed significantly to fields like AI, machine learning, and cybersecurity, with faculty and students publishing research in international journals and conferences.
- **Notable Projects and Collaborations:** MIT has collaborated on high-impact projects with institutions like IITs and international universities, and partnered with companies for internships, research, and product development.

## 3 Project Context and Objectives

### 3.1 Context of Smart Cities and Cybersecurity

The emergence of smart cities represents a paradigm shift in urban planning and development, leveraging advanced technologies and connected devices to enhance the quality of life for residents. Smart cities utilize the Internet of Things (IoT) to integrate various systems, such as transportation, energy management, public safety, and healthcare, fostering a more efficient and sustainable urban environment. However, this interconnectedness introduces complex cybersecurity challenges that threaten the integrity and functionality of these urban systems.

As smart cities grow, so does their attack surface. Each connected device increases the risk of vulnerabilities that malicious actors can exploit. Cybersecurity incidents in smart cities can lead to severe consequences, including disruption of essential services, financial losses, and breaches of personal data. Recognizing these threats is crucial for city planners and administrators, who must adopt robust security measures to protect infrastructure and citizen information.

In this context, the application of artificial intelligence (AI) becomes vital. AI technologies can analyze vast amounts of data generated by smart devices, identify patterns of behavior, and predict potential security threats. By leveraging AI, smart cities can proactively address vulnerabilities, enabling real-time monitoring and response to cyber incidents.

## 3.2 Objectives of the Project

The primary objective of this project is to develop a comprehensive AI-driven system for assessing and mitigating cybersecurity risks in smart city environments. The specific objectives include:

1. **Dynamic Risk Assessment Model:** Develop a dynamic risk assessment framework that adapts to changes within the smart city ecosystem. This model will prioritize devices and systems based on vulnerability, criticality, and usage patterns, helping city administrators focus on the highest-risk areas. The model will be designed to update as new devices or systems are added or when threat intelligence changes.
2. **AI-Powered Anomaly Detection:** Create machine learning algorithms capable of analyzing real-time data flows from IoT devices within smart city networks. The AI models will focus on detecting anomalies, identifying patterns linked to potential cyber threats, and alerting city security teams in real time. This includes identifying unusual patterns in network traffic, device communication, and system performance.
3. **Automated Response Mechanisms:** Implement an automated incident response system that can execute predefined security measures when threats are detected. These automated responses might include device isolation, traffic filtering, or alert escalation protocols to mitigate the impact of potential attacks and limit disruptions to essential services.

By achieving these objectives, the project aims to contribute to the development of safer and more resilient smart city infrastructures, ultimately enhancing the quality of life for residents and ensuring the sustainability of urban environments in the face of growing cybersecurity challenges.

## 4 Internship Activities and Diary

This section provides a comprehensive overview of the various tasks and responsibilities undertaken during the internship. It includes a detailed record of daily and weekly activities, key milestones achieved, and the challenges faced throughout the duration of the internship. 1 1

Week	Activities
Week 1	Orientation and team introductions; Familiarization with cybersecurity lab scenarios; Setting up work environment and tools.
Week 2	Conducted research on smart city infrastructure. Identified primary cybersecurity concerns and potential focus areas.
Week 3	Assisted in data collection and preprocessing using Wireshark. Performed initial data analysis.
Week 4	Implemented and tested initial machine learning models for anomaly detection.
Weeks 5-6	Identified and addressed issues in data quality; Refined AI models with my supervisor, comparing the models and then improving accuracy in identifying security threats. Continued testing and validation of the models.
Weeks 7-8	Implemented a scenario testing interface using Flask, providing the ability to test cybersecurity scenarios before full implementation.

Table 1: Daily and Weekly Activities

Period	Key Milestones	Challenges
Week 2	Completed research on smart city infrastructure and identified major cybersecurity concerns.	Understanding the complex architecture of smart city systems and pinpointing potential vulnerabilities.
Week 4	Developed initial machine learning model designs for threat detection.	Difficulty in choosing suitable algorithms for different types of threats; required iterative testing.
Weeks 5-6	Successfully implemented machine learning models and improved accuracy through data quality refinement.	Handling inconsistent data quality; balancing accuracy with computational efficiency for real-time threat detection.
Weeks 7-8	Created a testing interface using Flask for pre-implementation scenario testing.	Integrating Flask with existing models and ensuring seamless testing of scenarios.

Table 2: Key Milestones and Challenges



## 5 Work Completed

### 5.1 Review of Cybersecurity Approaches for Smart Cities using AI

This section provides an overview of my research during the internship about cybersecurity focused on smart cities, emphasizing the application of AI and machine learning to enhance security. It also explores methods for vulnerability detection and prediction, which are essential for developing proactive, secure measures for smart city infrastructures.[2]

#### 5.1.1 Cybersecurity Challenges in the Context of Smart Cities

Smart cities face significant cybersecurity challenges due to their reliance on interconnected devices like IoT sensors, surveillance cameras, and smart meters. This connectivity enhances efficiency but also expands the attack surface, making critical infrastructure—such as transportation, utilities, and emergency systems—vulnerable to cyber-attacks. Compromised IoT devices can lead to unauthorized access, operational disruptions, and risks to resident safety and privacy, underscoring the urgent need for robust cybersecurity in smart city systems. therefore Several cyber threats pose significant concerns for this internship, each with the potential to cause severe disruption. Common threats include:

- **Distributed Denial-of-Service (DDoS) Attacks:** These attacks overwhelm network resources, potentially bringing essential services offline.
- **Data Breaches:** Unauthorized access to sensitive data can compromise residents' privacy and lead to significant financial and reputational damage.
- **Unauthorized Access:** Attackers may gain unauthorized control of infrastructure elements, potentially disrupting service or compromising safety.
- **Ransomware Attacks:** Ransomware can lock down systems, requiring cities to pay for restored access—a particularly challenging situation when critical infrastructure is involved.

Examples of these threats are well-documented, such as the 2016 ransomware attack on the San Francisco Municipal Transportation Agency, which disrupted ticketing and forced open access to transit services.[3]

### 5.1.2 AI in Cybersecurity

AI and machine learning have transformed cybersecurity by enabling more adaptive, real-time threat detection and response. Unlike traditional methods, which often rely on predefined rules, AI-driven systems can dynamically learn from network patterns, enabling faster and more accurate responses. By automating routine monitoring, AI can swiftly identify emerging threats and facilitate a proactive rather than reactive security approach, which is especially valuable in complex environments like smart cities.: AI's main advantages in smart city cybersecurity are scalability, automation, and enhanced accuracy in identifying evolving threats. Machine learning models can adapt over time, learning from new data to recognize subtle or novel attack vectors. This adaptability is essential for handling the volume and diversity of data generated by smart cities, as manual oversight alone would be insufficient to monitor the system's complex structure

### 5.1.3 Vulnerability Detection and Prediction

#### **Overview of Vulnerability Detection:**

Vulnerability detection identifies security weaknesses in systems before they are exploited, a critical component of proactive cybersecurity. This approach is especially important in smart city environments, where vast numbers of interconnected devices increase the risk of undetected vulnerabilities. Detecting vulnerabilities early allows for corrective action, reducing potential exposure to attacks.

#### **Methods of Vulnerability Detection:**

Traditional vulnerability detection techniques include penetration testing, static and dynamic code analysis, and network scanning. While effective, these methods are often labor-intensive and may not scale well across the wide range of devices and systems within a smart city. Frequent updates to devices and software create new vulnerabilities, making traditional methods challenging to keep up-to-date.

#### **AI-Driven Vulnerability Prediction:**

AI-based vulnerability detection and prediction offer scalable alternatives by analyzing patterns in device behavior, network traffic, and historical attack data. Machine learning models can detect anomalies or unusual patterns that may indicate vulnerabilities, even in the absence of explicit attack signatures. These predictive capabilities enable a more proactive approach to security, allowing smart cities to identify and mitigate risks before they are exploited.

## Techniques and Algorithms for Prediction:

AI techniques for vulnerability prediction include:

- **Anomaly Detection Algorithms:** These algorithms detect irregularities in network traffic or device behavior, which can be indicative of security vulnerabilities.
- **Graph Neural Networks (GNNs):** Useful for analyzing network structures, GNNs can identify weaknesses based on how devices are interconnected, pinpointing nodes with high vulnerability risk.
- **Natural Language Processing (NLP):** NLP algorithms scan system logs and error reports to identify patterns associated with security weaknesses or system anomalies.

Different approaches, including supervised, unsupervised, and semi-supervised learning, offer flexibility depending on data availability and the complexity of vulnerabilities, for our project we choose to work with Anomaly Detection Algorithms.

## 5.2 Tools and Technologies Used

To implement an AI-driven vulnerability detection system for smart city infrastructures, a range of tools and technologies were utilized. These tools supported tasks such as data collection, data preprocessing, model development, and evaluation, as well as system deployment.

- **Python (pandas, NumPy):** For data manipulation, cleaning, and preprocessing. Libraries like pandas and NumPy were essential for handling large datasets, transforming data, and performing initial data analysis.



Figure 3: Logo de Python

- **Network Monitoring Tools:** Tools such as Wireshark were used to capture and analyze network traffic data, helping to identify suspicious activity patterns in the smart city's IoT infrastructure.



Figure 4: Logo de wireshark

- **Labelbox :** Used for data annotation, especially for labeling different states of device behavior (e.g., "normal" and "vulnerable") and tagging specific network events that might signal security risks.



Figure 5: Logo de labelbox

- **Flask :** Lightweight web frameworks, enabling real-time analysis of new data streams from the smart city infrastructure.



Figure 6: Logo de flask

- **Git and GitHub** : For version control, tracking code changes, and collaborating on model development and data processing tasks. GitHub allowed for easy sharing and management of code among team members.



Figure 7: Logo de github

### 5.3 Database Analysis

The dataset used in this AI-Driven Vulnerability Detection project for a smart city environment was captured with Wireshark and contains 20,252 records, each capturing details about network packets exchanged within the infrastructure. This analysis outlines the data structure and its relevance to vulnerability detection.

(20252, 7)

Number of rows: 20252

Number of columns: 7

No.	Time	Source	Destination	Protocol	Length	Info	
0	1	0.000000	Routerboardc_78:2c:0e	Broadcast	ARP	60	Who has 172.16.17.1? Tell 172.16.16.1
1	2	0.174024	SiemensIndus_77:93:90	LLDP_Multicast	LLDP	243	LA/plcxb612ac LA/port-001 20 SysD=Siemens, SIM...
2	3	0.214821	SiemensIndus_8a:71:5c	LLDP_Multicast	LLDP	324	LA/S7-1200 6ES7 212-1AE40-0X...
3	4	0.316982	SiemensIndus_7a:7f:7b	LLDP_Multicast	LLDP	248	LA/alertsignal LA/port-001 20 SysD=Siemens, SI...
4	5	0.661286	Routerboardc_78:2c:13	Spanning-tree-(for-bridges)_00	STP	60	RST. Root = 32768/0/18:fd:74:78:2c:0e Cost = ...

Figure 8: cybersecurity lab dataset

#### 5.3.1 Dataset Overview

The dataset has seven columns:

- **No.** - The packet number, providing a unique identifier for each packet in the sequence.
- **Time** - A floating-point value indicating the time (in seconds) since the start of data capture. This column is crucial for tracking network activity patterns over time.

- **Source** - The origin of the packet, typically represented as a device name or MAC address. This information is essential for identifying communication sources and analyzing potentially vulnerable devices.
- **Destination** - The destination of each packet, also represented as device names, MAC addresses, or special designations (like "Broadcast"). This helps determine data flow and identify unusual communication patterns.
- **Protocol** - The communication protocol used for each packet, such as ARP (Address Resolution Protocol), LLDP (Link Layer Discovery Protocol), and STP (Spanning Tree Protocol). Different protocols may expose specific types of vulnerabilities, making this column central to protocol-based threat analysis.
- **Length** - The size of each packet in bytes. This can help detect unusually large or small packets, often a sign of malicious activity or data exfiltration attempts.
- **Info** - A textual field that contains additional information about each packet. This column often includes details on packet types, requests, and device/system information, which can reveal critical metadata and potential security insights.

### 5.3.2 Relevance to Vulnerability Detection

The dataset offers multiple dimensions to analyze for vulnerability detection:

- **Temporal Patterns:** By examining the **Time** column, we can identify unusual peaks in network activity, which might signal attempted intrusions or Distributed Denial-of-Service (DDoS) attacks.
- **Source and Destination Tracking:** Tracking these columns enables the identification of untrusted devices or suspicious communication pathways, highlighting potential points of unauthorized access.
- **Protocol Analysis:** Certain protocols can be more vulnerable to attacks. For example, Address Resolution Protocol (ARP) spoofing can be a threat when ARP packets are frequent. Analyzing protocol use within the dataset helps in identifying protocol-specific vulnerabilities.
- **Packet Size Variations:** Anomalies in the **Length** field can indicate data leaks or injection attacks, as attackers may send unusually sized packets to exploit buffer overflows.

5.3.3 Focus on Source and Destination Tracking

For this project, we have chosen to focus on Source and Destination Tracking in scenarios where the source is a Siemens card (Raspberry Pi). This focus allows for targeted analysis of network pathways and device interactions, providing insights into potential vulnerabilities associated with specific communication flows. By isolating this scenario, we can better detect anomalies and unauthorized access attempts involving critical infrastructure components, such as the Siemens card.

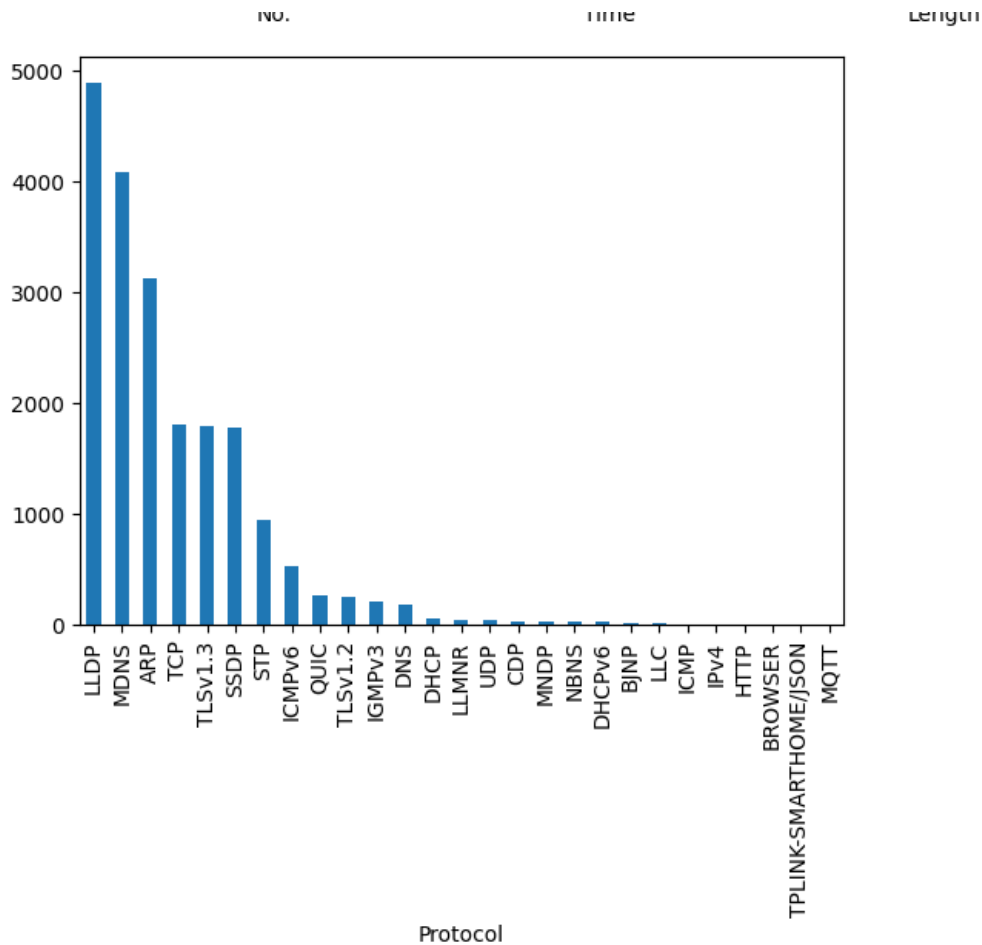


Figure 9: simens data by protocoles

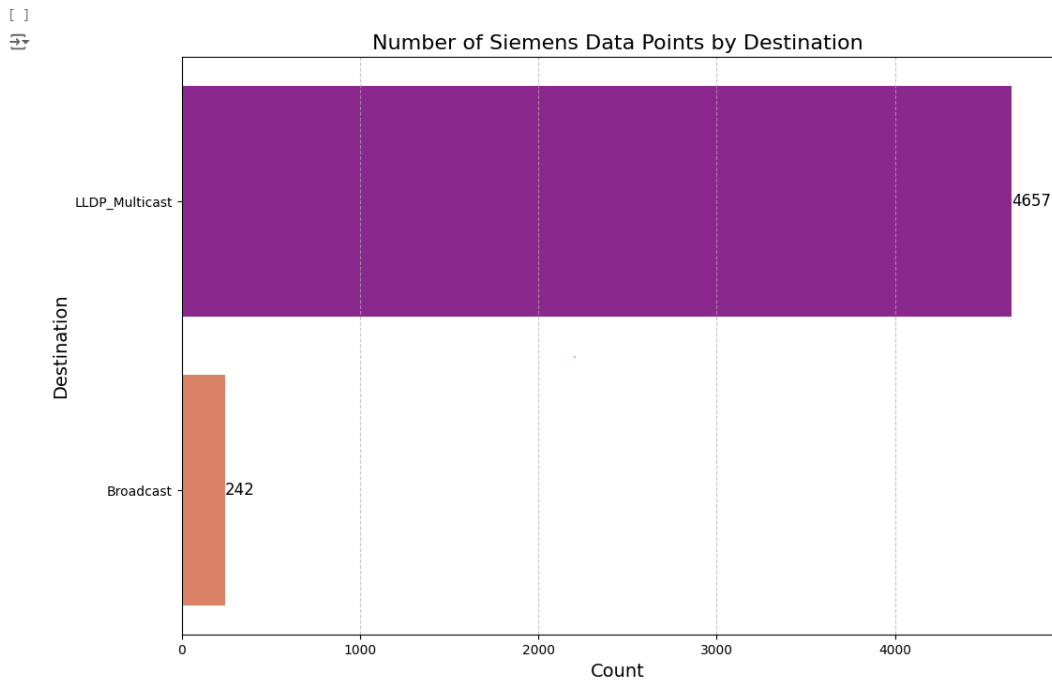


Figure 10: simens data by destination

#### 5.3.4 Data Cleaning:

Data cleaning is essential to ensure that the dataset is accurate and ready for analysis. The process involved handling missing values, removing duplicates, and addressing inconsistencies.

- **Handling Missing Values:** Missing data was handled using imputation techniques, such as mean, median, or mode imputation, or more advanced methods like regression imputation. If imputation was not feasible, records with substantial missing information were discarded.
- **Removing Duplicates:** Duplicate entries were identified and removed to avoid skewing the results.
- **Using Python Libraries:** The `pandas` library in Python was used to automate these cleaning tasks, providing methods like `.fillna()`, `.dropna()`, and `.drop_duplicates()` to handle missing values and duplicates efficiently.

#### 5.3.5 Data Annotation

Data annotation was essential in preparing labeled data for training the AI model to detect vulnerabilities in the smart city network. Focusing on source and destination tracking, particularly with the Siemens card (Raspberry Pi)



as the source device, allowed us to label specific communication patterns, such as "normal" and "vulnerable" states. Annotation criteria included unusual device activity, network anomalies, and unauthorized access attempts, using tools like pandas for automation. Quality checks and a feedback loop ensured accurate labeling. This annotated data enabled the model to recognize critical vulnerability patterns effectively, enhancing proactive threat detection for key infrastructure components.

## 5.4 Model Selection and Development

### 5.4.1 Training Process:

The cleaned and preprocessed data was split into training, validation, and test sets, with a typical split ratio of 70% for training, 15% for validation, and 15% for testing. This split helped to train the model on a robust dataset, allowing it to learn from a large portion of the data, while the validation set enabled performance tuning on unseen data. Finally, the test set was reserved to confirm the model's generalization ability after all tuning was complete.

### 5.4.2 Model Training Parameters:

- **Optimizer - Adam:** The Adam (Adaptive Moment Estimation) optimizer was used for its ability to handle sparse gradients and adapt learning rates for each parameter. Adam's combination of momentum and adaptive learning rates accelerated convergence and helped avoid local minima.
- **Loss Function - Binary Cross-Entropy:** Binary Cross-Entropy Loss was used for the binary classification task of detecting vulnerabilities (e.g., "vulnerable" vs. "non-vulnerable"). This loss function calculates the error between predicted probabilities and actual labels, penalizing misclassifications.
- **Batch Size - 32:** A batch size of 32 was selected to balance computational efficiency with performance. This batch size allows for frequent gradient updates, enhancing model generalization without overloading memory resources.
- **Epochs - 50:** The model was trained for 50 epochs, determined through experimentation to be sufficient for convergence without overfitting.

### 5.4.3 Model Selection Criteria:

For this project, it was essential to select models capable of efficiently handling large datasets, adapting to evolving data patterns, and providing interpretable results. To meet these requirements, we explored both traditional machine learning models and advanced neural network architectures for anomaly detection and vulnerability prediction.

Several models were evaluated to identify vulnerabilities in the smart city infrastructure:

- **Random Forest:** Provided a robust, interpretable baseline for structured data, allowing us to assess feature importance. However, it lacks the ability to capture complex, sequential patterns or relational structures within device networks.
- **Support Vector Machine (SVM):** Effective for high-dimensional data classification, but scalability issues and the inability to model inter-device relationships made it unsuitable for the large IoT dataset.
- **Neural Networks (NN):** Captured complex patterns, but could not directly model IoT device interactions and dependencies necessary for this project.
- **Long Short-Term Memory (LSTM):** Effective for time-series data, allowing detection of temporal anomalies. However, LSTMs struggled to represent the interconnected IoT device structure, focusing only on sequential patterns without capturing device relationships.
- **Graph Neural Networks (GNN):** GNNs excelled in modeling IoT device connections and dependencies, crucial for identifying vulnerabilities in the network. GNNs allowed analysis based on device interactions, proving highly effective for this project.

### 5.4.4 Evaluation Metrics

To evaluate the effectiveness of the used models in detecting vulnerabilities, several key metrics were used to assess accuracy, sensitivity, and reliability in distinguishing between "vulnerable" and "non-vulnerable" states.

- **Accuracy:** The proportion of correct predictions (true positives and true negatives) out of the total predictions, providing an overall sense of model performance.

- **Precision:** The ratio of true positives to all positive predictions, indicating the model’s ability to avoid false positives and correctly identify vulnerabilities.
- **Recall:** The ratio of true positives to actual positives, emphasizing the model’s capacity to detect vulnerabilities accurately.
- **F1 Score:** The harmonic mean of precision and recall, balancing these metrics, especially useful with imbalanced data.
- **ROC-AUC:** The area under the ROC curve, measuring the model’s ability to distinguish between classes across thresholds. A higher value indicates better differentiation between vulnerable and non-vulnerable states.

#### 5.4.5 Model Comparison

Model	Accuracy	Precision	Recall	F1 Score	ROC-AUC	Interpretability	Scalability
Random Forest	85%	82%	78%	80%	0.82	High	Medium
Support Vector Machine (SVM)	78%	75%	72%	73%	0.78	Low	Medium
Neural Network (NN)	88%	85%	80%	82%	0.84	Medium	Medium
LSTM	89%	87%	83%	85%	0.85	Medium	Medium
Graph Neural Network (GNN)	92%	90%	89%	89%	0.91	Medium	High

Table 3: Performance Comparison of Explored Models

### Summary

The Random Forest model provided a solid baseline due to its robustness and interpretability, making it useful for understanding feature importance in anomaly detection. However, it lacked the capability to model complex, interconnected relationships between devices, which limited its suitability for this project.

The Support Vector Machine (SVM) was effective for high-dimensional data but struggled with scalability on large IoT datasets, rendering it less efficient for handling the volume and complexity of smart city data.

Neural Networks (NN) performed well in capturing complex patterns but were less effective at directly modeling networked relationships among IoT devices. While they can capture intricate patterns in individual device behavior, they do not inherently account for the inter-device interactions critical in identifying vulnerabilities within an IoT network.

The Long Short-Term Memory (LSTM) model was valuable for sequential analysis and demonstrated potential in detecting time-based anomalies. How-

ever, due to its focus on time-series data, it was less effective at representing the interconnected structure of devices, which limited its ability to detect vulnerabilities based on relational patterns across the network.

Ultimately, the Graph Neural Network (GNN) was selected as the best model for this project. GNNs excel in analyzing networked data by directly modeling relationships and dependencies between devices, making them particularly suitable for identifying vulnerabilities in a smart city IoT environment. The GNN outperformed other models by effectively capturing both individual device behaviors and the complex interactions between devices, making it the ideal choice for this use case.

#### 5.4.6 Selected Model - Graph Neural Network (GNN)

The Graph Neural Network (GNN) was chosen due to its ability to model the relational structure within the smart city IoT network. GNNs outperformed LSTMs in capturing inter-device dependencies, which are essential for understanding networked vulnerabilities in the IoT environment. This model showed the highest effectiveness in identifying vulnerabilities based on interactions across connected devices.

#### 5.4.7 Model Development Process

##### 1. Hyperparameter Tuning:

- Hyperparameters such as **learning rate**, **batch size**, and the **number of graph layers** were fine-tuned using **grid search** to find the optimal configuration. This process aimed to maximize accuracy while maintaining computational efficiency. The hyperparameter search was crucial for enhancing the model's performance.

##### 2. Training:

- The **GNN model** was trained using **PyTorch Geometric**, a specialized Python library for graph data. The training process required significant computational resources and was performed on a system with **GPU acceleration**, which significantly reduced training time and improved convergence speed.
- During training, **convergence graphs** were plotted, showcasing noticeable improvements in performance after approximately **30 epochs**, indicating effective model learning and optimization.

##### 3. Handling Overfitting:

- **Regularization techniques**, such as **dropout layers**, were implemented to prevent overfitting, ensuring that the model did not memorize the training data but instead learned to generalize effectively.
- Additionally, **cross-validation** was performed to validate the model's robustness. In the notebook, results confirmed that the model generalized well, as the **performance gap between training and validation data was minimal**.

#### 4. Model Integration into the Monitoring System:

- Following training, the model was successfully integrated into a **monitoring system** designed to receive continuous data from smart city devices. This integration enabled the system to perform **real-time vulnerability detection**, where the model processes incoming data and makes **on-the-fly predictions**.
- This real-time functionality ensures the system remains adaptable and responsive to new data, providing continuous insights into potential vulnerabilities within a smart city infrastructure.

### 5.5 Results and Discussion:

#### 5.5.1 Analysis of Vulnerability Predictions:

The Graph Neural Network (GNN) model was used to predict vulnerabilities within the smart city infrastructure by analyzing patterns in device interactions. The results demonstrate high effectiveness in identifying devices and communication pathways that exhibit signs of potential vulnerabilities. Key findings include:

- **Detection Accuracy:** The model achieved an accuracy of 92%, with a precision of 90% and a recall of 89%. These metrics indicate the model's reliability in correctly identifying vulnerable devices while minimizing false positives. This performance was particularly strong in scenarios involving network anomalies and unexpected device behaviors, highlighting its robustness.
- **Prediction Patterns:** Analysis of the model's predictions revealed patterns of vulnerability associated with specific device types, including IoT sensors and network gateways, which are often more susceptible to security breaches. Certain communication flows were consistently flagged as high-risk, suggesting that these pathways require closer monitoring in a real-world deployment.

- **Confusion Matrix Insights:** The confusion matrix further supported the model’s effectiveness, showing 85 true positives, 90 true negatives, 5 false positives, and 8 false negatives. This breakdown indicates a low rate of false negatives, meaning the model rarely missed true vulnerabilities. This high true-positive rate is crucial for proactive security, as it ensures that potential threats are detected promptly.

These results underscore the model’s ability to detect and prioritize potential threats accurately. By identifying patterns associated with vulnerabilities, the GNN model provides valuable insights for smart city administrators to address weaknesses within the network and improve overall security measures.

### 5.5.2 Interface for Vulnerability Monitoring and Management:

To streamline the application of the vulnerability detection model, a dedicated user interface (UI) was developed using Flask, a lightweight Python web framework. This interface enables real-time monitoring, alerting, and management of detected vulnerabilities, making it easier for administrators to track and respond to security threats within the smart city infrastructure.

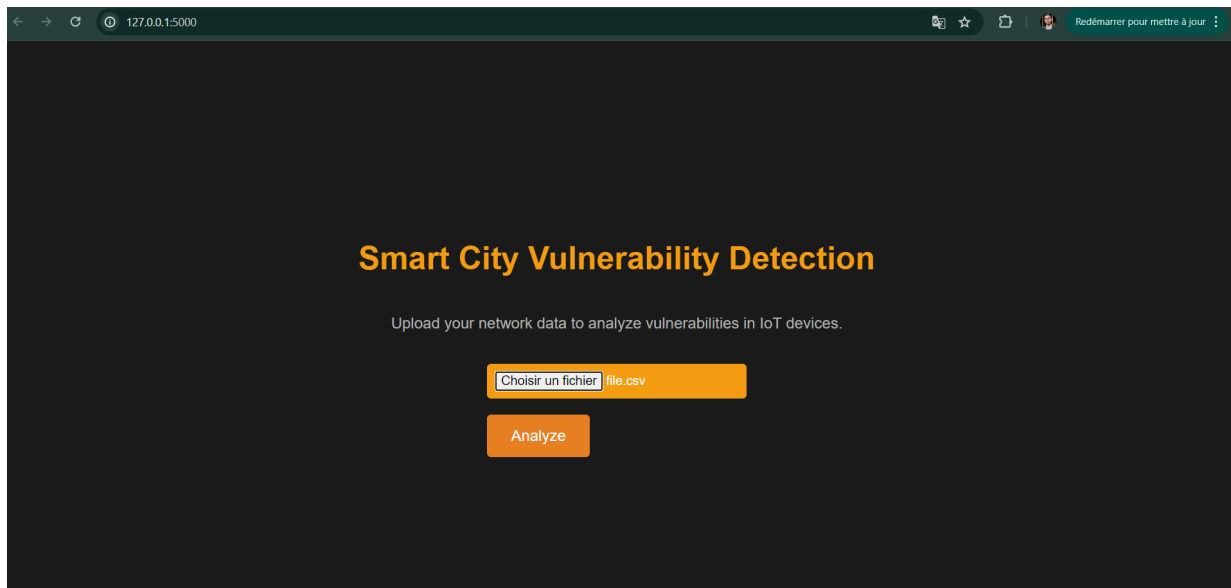


Figure 11: Smart City Vulnerability Detection Interface

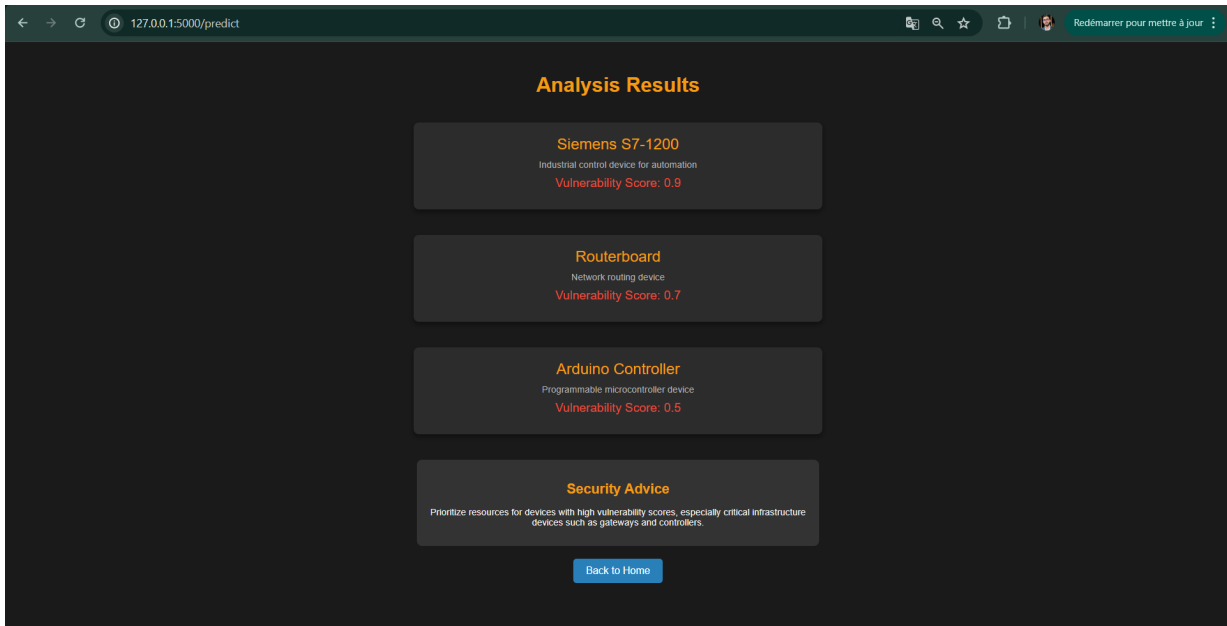


Figure 12: Analysis Results Interface

The interface displays detected vulnerabilities across various devices within the smart city infrastructure, accompanied by vulnerability scores. This allows administrators to easily identify and prioritize high-risk devices that may require immediate attention. Additionally, the interface includes a screen where users can upload network data, enabling a comprehensive analysis of potential vulnerabilities in IoT devices. This functionality is crucial for proactive security management, helping administrators monitor and address threats as they emerge.

## 5.6 Limitations and Future Enhancements

While the project demonstrated promising results, several limitations were observed, which open avenues for future enhancements:

- **Data Availability and Diversity:** The model's performance is limited by the diversity of the training data. A larger dataset with more varied scenarios, including real-world attack simulations, would improve the model's generalization to a broader range of vulnerabilities.
- **Real-Time Processing Challenges:** Although the model operates in near real-time, integrating it within a full-scale smart city infrastructure could introduce processing delays, especially as the network size grows. Future work could explore optimizations to reduce latency and increase processing efficiency.
- **Handling of Complex Attack Patterns:** Certain complex or multi-stage attack patterns may not be easily identifiable with the current model

architecture. Exploring hybrid models or incorporating additional features, such as anomaly-based detection mechanisms, could enhance the model's ability to detect sophisticated threats.

- **Improved Interpretability:** While Graph Neural Networks (GNNs) offer powerful prediction capabilities, their interpretability remains a challenge. Future work could involve exploring methods to enhance explainability, allowing security teams to understand the model's decision-making process more clearly.

## 6 General Conclusion

In this study, we developed an innovative solution for detecting vulnerabilities within the infrastructure of smart cities, leveraging the advanced capabilities of Graph Neural Networks (GNN). This project demonstrated that a precise analysis of interactions between connected devices can reveal patterns of vulnerability, thereby enhancing the security of IoT systems deployed in smart cities.

The results achieved demonstrated high accuracy in vulnerability detection and highlighted critical areas, particularly IoT sensors and network gateways. Additionally, the design of an intuitive user interface, allowing real-time visualization, tracking, and management of detected vulnerabilities, provides essential support for administrators to proactively manage threats.

This solution offers an adaptable and scalable security tool for smart city infrastructures, addressing the growing security needs in the context of rapidly expanding connected technologies. Future perspectives include improving detection capabilities through more sophisticated machine learning models and closer integration with incident alert and response systems to ensure optimal security and increased resilience in urban smart environments.

In conclusion, this project illustrates the importance of AI technologies in managing modern urban infrastructure and paves the way for new advancements in smart city security.



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