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THEME

Detecting Malware In IoT Devices

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Dedication 1

First and foremost, all praise and thanks are due to Allah, abundant in blessings and goodness, who granted me the ability and opportunity to achieve this accomplishment. Through His grace, I have overcome challenges and achieved my goals.

I render my sincere appreciation to my mother and father, who have unfailingly offered their support and have been my constant allies. I am indebted to them for all the sacrifices they've made for my well-being. 'This triumph is rightfully theirs; I am just a means '. My thankfulness to them knows no bounds.

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Babziz Mohamed Youcef

Dedication 2

In the name of God, and peace and blessings be upon our Master, the Messenger of God.

First, we thank God Almighty for granting us the strength, patience, determination, and success to complete this work.

We also thank God for the blessing of my parents, who spared no effort in supporting me. I am indebted to them for all the sacrifices they made and appreciate their commitment to my completion of my studies.

Djaborebbi Souhaib

Abstract:

The rapid proliferation of Internet of Things (IoT) devices has led to significant security challenges, particularly with regard to malware attacks. Due to their limited computing resources, diverse architectures, and often weak security measures, IoT devices are increasingly vulnerable to malicious attacks. Traditional malware detection techniques, designed for traditional computing systems, are often ineffective in IoT environments. This paper explores modern approaches to malware detection on IoT devices, using the Random Forest algorithm in machine learning. The model was tested on two different sized datasets, yielding good results, demonstrating its effectiveness in detecting malware on these devices.

Keywords: Internet Of Things, Random forest, Botnet Attack, Machine learning, Deep learning .

ملخص:

أدى الانتشار السريع لأجهزة إنترنت الأشياء (IoT) إلى تحديات أمنية كبيرة، لا سيما فيما يتعلق بهجمات البرمجيات الخبيثة. ونظرًا لمحدودية مواردها الحاسوبية، وتنوع بنيتها، وضعف إجراءاتها الأمنية في كثير من الأحيان، تتعرض أجهزة إنترنت الأشياء لهجمات خبيثة بشكل متزايد. وغالبًا ما تكون تقنيات الكشف عن البرمجيات الخبيثة التقليدية، المصممة لأنظمة الحوسبة التقليدية، غير فعالة في بيئات إنترنت الأشياء. تستكشف هذه الورقة البحثية الأساليب الحديثة للكشف عن البرمجيات الخبيثة على أجهزة إنترنت الأشياء، باستخدام خوارزمية Random Forest في التعلم الآلي تم إعتماد مجموعتين مختلفتي الحجم من البيانات على النموذج فتحصلنا على نتائج جيدة حيث اثبت النموذج كفاءته في الكشف عن البرمجيات الخبيثة في هذه الأجهزة.

الكلمات المفتاحية: إنترنت الأشياء, الشجرة العشوائية, هجوم بوت نت, التعلم الآلي, التعلم العميق.

Résumé:

La prolifération rapide des objets connectés (IoT) a engendré d'importants défis de sécurité, notamment en matière d'attaques de logiciels malveillants. En raison de leurs ressources informatiques limitées, de la diversité de leurs architectures et de la faiblesse de leurs mesures de sécurité, les objets connectés sont de plus en plus vulnérables aux attaques. Les techniques traditionnelles de détection des logiciels malveillants, conçues pour les systèmes informatiques traditionnels, sont souvent inefficaces dans les environnements IoT. Cet article explore les approches modernes de détection des logiciels malveillants sur les objets connectés, en utilisant l'algorithme Random Forest en apprentissage automatique. Ce modèle a été testé sur deux ensembles de données de tailles différentes et a donné de bons résultats, démontrant son efficacité à détecter les logiciels malveillants sur ces appareils.

Mots-clés: Internet Of Things, Random forest, Botnet Attack, Machine learning, Deep learning.

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List of Acronyms:

IoT:	**Internet of Things.**
ITU:	**International Telecommunication Union**
ML:	**Machine Learning**
RFID:	**Radio Frequency Identification**
M2M:	**Machine-to-Machine**
FL:	**Federated Learning**
DL:	**Deep learning**
RF:	**Random Forest**
KNN:	**K-nearest Neighbor**
DoS:	**Denial of Service**
DDoS:	**Distributed Denial-of-Service**
MiTM:	**Man-in-the-Middle Attack**

Introduction General

Over the past few years, the Internet of Things (IoT) has rapidly evolved and become the dominant technology worldwide. IoT connects hundreds of millions heterogenous smart objects (e.g., sensors, actuators, smart thermostats, smart lights) to each other and to the Internet to exchange real-time data using various communication protocols. IoT applications such as smart homes, smart cities, smart health, smart learning, and smart transportation have a direct impact on numerous aspects of our daily lives.

The Internet of Things (IoT) has revolutionized industries through interconnected devices, but due to their insecure protocols and resource constraints they are targeted by malware.

Moreover, smart objects capture, process, and store a huge amount of sensitive data which can be exposed by malware resulting in privacy violations and data theft. Malware attacks have witnessed dramatical growth in recent years. According to SonicWall cyber threat report, in the first half of 2023 IoT malware increased by 37 % compared to the first half of 2022, resulting in 77.9 million attacks. This illustrates how harmful malware can be and how much damage they can cause. Thus, detecting and classifying IoT Malware is critical task to mitigate security risks.

Traditional Malware detection techniques (such as signature-based) are insufficient and inefficient for IoT malware detection due to the fast grow in the number of smart objects, the diversity of smart objects, and the complexity of communication protocols. Machine Learning (ML) and Deep Learning (DL) algorithms and techniques are widely used nowadays and have potentials to handle complex tasks. Indeed, traditional ML methods are not perfectly suitable to deal with IoT malware. First, malware classification needs large computational resources to run complex algorithms, which is not applicable in IoT environments where smart objects are resource-constrained. Second, the significant surge in malware development (956 new malware were developed per day in 2023) requires real-time detection and classification. Developing models to detect and classify IoT Malware is a crucial task.

To address those issues, there is an urgent need to develop novel lightweight ML approaches that are specifically designed for IoT malware classification and mitigation of IoT cyber threats. Lightweight ML malware classification techniques can deliver accurate and high-speed real-time malware classification with minimal computing overhead and complexity by optimizing dimensionality reduction techniques (feature extraction, feature selection) and classification models. Moreover, lightweight ML models are scalable which enable them to discover newly developed malware and Zero-day attacks . Furthermore, lightweight ML technique are interoperable with various systems and architectures. Thus, they are appropriate for use for IoT environments and the resource constraint smart objects.

In this paper we will study the Internet of Things and malware in IoT devices, and then try to present a method for detecting this malware.

Chapter 1: Overview of the internet of things

I. Chapter 1: Overview of the internet of things

I.1 Introduction:

Evolution of internet began by connecting computers. Later many computers were connected together which created World Wide Web. Then mobile devices were able to connect to the internet which leads to mobile-Internet technique. People started using the internet via social networks. Finally the idea of connecting daily objects to the internet was proposed, which lead to the Internet of Things technology.

First time the term ―Internet of Things: word was used by Kevin Ashton in a presentation during 1998 . He has mentioned ―The Internet of Things has the potential to change the world, just as the Internet did May be even more so. Later during 2001, MIT AutoID Lab center presented their view on IoT. Then during 2005, this is formally recognized by the International Telecommunication Union (ITU). **[1]**

I.2 Definition Of IoT:

IoT is considered as the networked connection of physical objects or devices. One of the definition of IoT by a researcher [*Somayya Madakam, R. Ramaswamy, Siddharth Tripathi*] *, Is* an open and comprehensive network of intelligent objects that have the capacity to auto-organize, share information, data and resources, reacting and acting in face of situations and changes in the environment.**[1]**

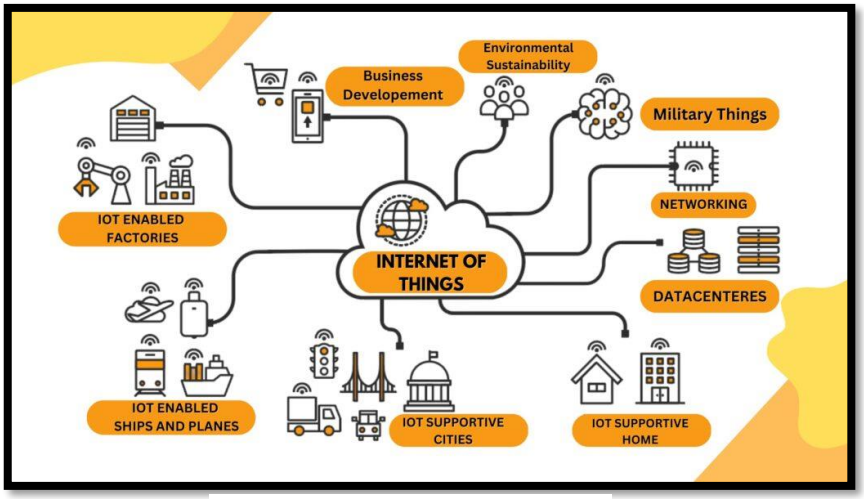

Figure 1: Internet Of Things

I.3 Architecture Of IoT:

There is no single consensus on architecture for IoT, which is agreed universally. Different architectures have been proposed by different researchers.

We choose to talk about the four-layer IoT architecture as it is the most common:

- **Perception Layer:** It is considered the first layer, and it is called physical layer , which has sensors for sensing and gathering information about the environment. It senses some physical parameters or identifies other smart objects in the environment.**[3]**
- **Gateway/Network Layer:** This layer is responsible for transferring the information collected by sensors to the next layer. It should support scalable, flexible, standards universal protocol for transferring data from heterogeneous devices (Different types of sensor nodes). This Layer should have high performance and robust network. It should also support multiple organizations to communicate independently.**[1]**
- **Middleware Layer:** Also known as processing layer, The data processing layer, sometimes referred to as the middleware layer, stores, analyzes, and pre-processes the data coming from the transport layer. This includes such activities as data aggregation, protocol translation, and security enforcement to ready data for the application layer. In addition, message brokers, IoT platforms, and edge computing nodes may also be included in this layer.**[4]**
- **Application Layer:** This is the top most layer of IoT which provides a user interface to access various applications to different users. The applications can be used in various sectors like transportation, health care, agriculture, supply chain, government, retail etc.**[1]**

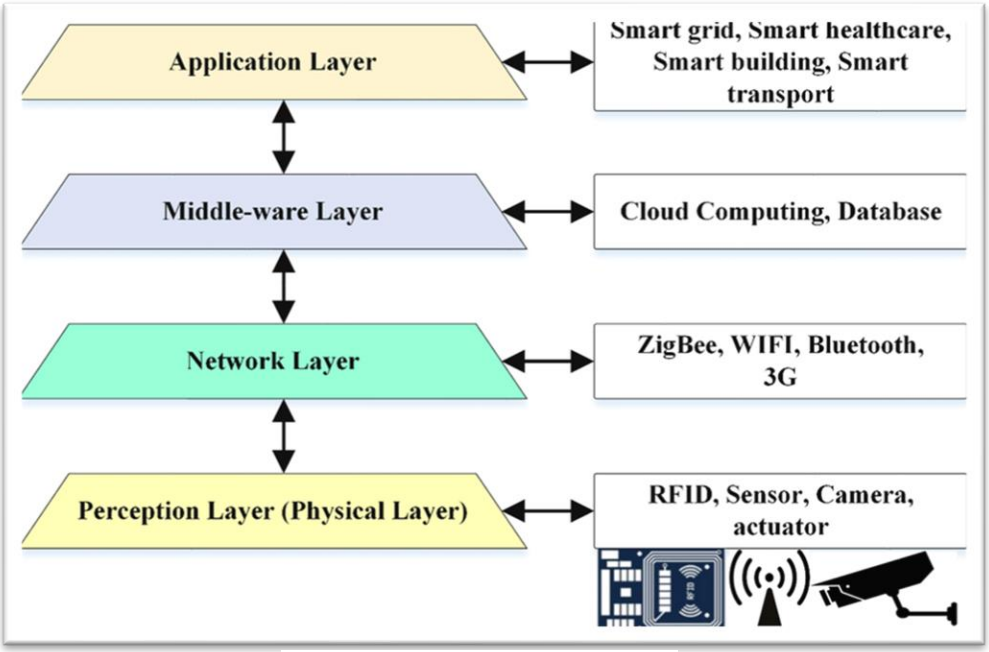

Figure 2 : IoT Architecture

I.4 Resources Limitation:

Resource limitations are a fundamental challenge in IoT systems. While IoT devices are designed to be lightweight and efficient, these limitations often require compromises in:

I.4.1 Processing, storage, energy and bandwidth constraints:

Processing, storage, and power constraints pose significant challenges in the Internet of Things (IoT). As the processing power of devices increases, power consumption increases, requiring effective management. IoT devices must balance processing and storage capabilities, while power consumption plays a key role in resource optimization.**[5]**

I.4.2 Device addressing:

Given the massive growth of IoT devices, the need to assign a unique identifier to each device, and the heterogeneity of IoT systems and their security needs, addressing is complex. IPv4 is insufficient to handle the massive number of IoT devices, making IPv6 a better alternative for addressing, internal security.**[5]**

I.4.3 Standardization:

Standardization in the Internet of Things (IoT) is crucial for efficient data collection, aggregation, dissemination, and distribution. The lack of unified standards, especially in Machine-to-Machine (M2M) communication, creates challenges for interoperability and scalability. There is a strong need for optimized standard interfaces and architectures that can ensure seamless connectivity, effective data management, and support the diverse applications within the IoT environment.

I.4.4 Security algorithms:

Security algorithms in the Internet of Things (IoT) are essential to ensuring data protection, privacy, and authentication, starting from the manufacturer, application, and protocol design. Due to the integration of sensors and radio frequency identification (RFID) tags, IoT systems become vulnerable to security threats. Therefore, lightweight, low-power, and secure security protocols are essential to maintain the confidentiality, integrity, and secure communications of IoT devices.

I.5 Elements of the Internet of Things:

I.5.1 Identification:

Identification in the context of IoT refers to the process of identifying and distinguishing particular devices or objects within a network. This component is critical for effective communication, data management, and control in IoT systems. To identify devices and enable smooth interaction, a variety of identification mechanisms are used, such as unique identifiers, tags, and addresses. These identification mechanisms ensure that data created by IoT devices is appropriately credited, recorded, and managed across the whole network.

Identification also makes it easier to implement security features like access control, authentication, and encryption to safeguard data integrity and privacy. Overall, robust identification techniques.**[6]**

I.5.2 Communication:

This element plays a crucial role in IoT by enabling access to cloud services. It serves as the channel through which data sensed by machines is transmitted to cloud-based platforms for further analysis and processing. This smooth data flow supports real-time monitoring, analytics, and responsive decision-making, allowing IoT applications to adapt efficiently to dynamic conditions. Reliable communication protocols and technologies ensure consistent data exchange between IoT devices and the cloud, promoting optimal resource utilization and enabling the scalability of IoT deployments. Ultimately, communication forms the backbone of IoT systems, empowering them to harness the capabilities of cloud computing for enhanced functionality and intelligence.**[7]**

I.5.3 Devices/sensors:

The Internet of Things (IoT) depends extensively on devices and sensors to collect and transmit data across various environments. These devices are equipped with diverse sensors capable of capturing real-time information, such as temperature, humidity, motion, and light levels. Actuators, in turn, use this sensor data to interact with their physical surroundings, while built-in communication technologies allow seamless network connectivity and data exchange. Modern sensors are designed to be energy-efficient and support wireless communication, making them well-suited for continuous operation. Together, these components form the hardware foundation of IoT systems, enabling real-time monitoring, analysis, and automated responses. This infrastructure supports a wide range of smart applications, including those in healthcare, agriculture, and urban development **[8]**.

I.5.4 Cloud-based capture and consolidation:

Cloud-based capture and consolidation involve the systematic collection, storage, and processing of data from diverse Internet of Things (IoT) devices and sensors using cloud computing infrastructure. This method offers numerous advantages, including scalability to

handle large volumes of data and ample storage capacity to manage the massive datasets generated by IoT systems. Cloud platforms provide robust computational power, enabling advanced data analysis and real-time processing.

One of the key benefits of cloud integration is universal data accessibility, allowing for efficient remote monitoring and management of IoT devices from virtually any location.

By consolidating data from multiple sources into a centralized platform, organizations gain more comprehensive insights that support better decision-making. Additionally, cloud solutions are cost-effective, eliminating the need for extensive on-premise hardware while offering powerful built-in security measures such as data encryption and access control to ensure data privacy and integrity.

Cloud environments also support real-time analytics, facilitating instant interpretation and response to incoming data. Moreover, automated backup and recovery mechanisms enhance data reliability and minimize the risk of loss, further strengthening the security and resilience of IoT deployments.**[9]**

I.5.5 Services:

IoT applications offer a wide range of services that can be categorized into four main types, First, **identity-related services** are essential for recognizing and verifying the identities of objects that initiate network interactions. Second, **information aggregation services** focus on collecting and processing data from multiple sources to generate meaningful insights. Third, **collaborative-aware services** utilize the aggregated data to support decision-making processes and deliver appropriate responses to connected devices. Lastly, **ubiquitous services** demonstrate the ability to respond dynamically and efficiently, unrestricted by time or location, enabling real-time interaction with devices as situations demand **[10]**.

I.5.6 Semantics:

The core function of IoT is to assist users by performing tasks on their behalf. This component is one of the most vital elements in IoT systems, as it is responsible for executing operations. Often referred to as the "brain" of the Internet of Things, it receives data from connected devices, processes the information, and makes intelligent decisions. Based on this analysis, it then sends appropriate responses or commands back to the devices to perform specific actions **[11]**.

I.6 The Challenges of the Internet of Things:

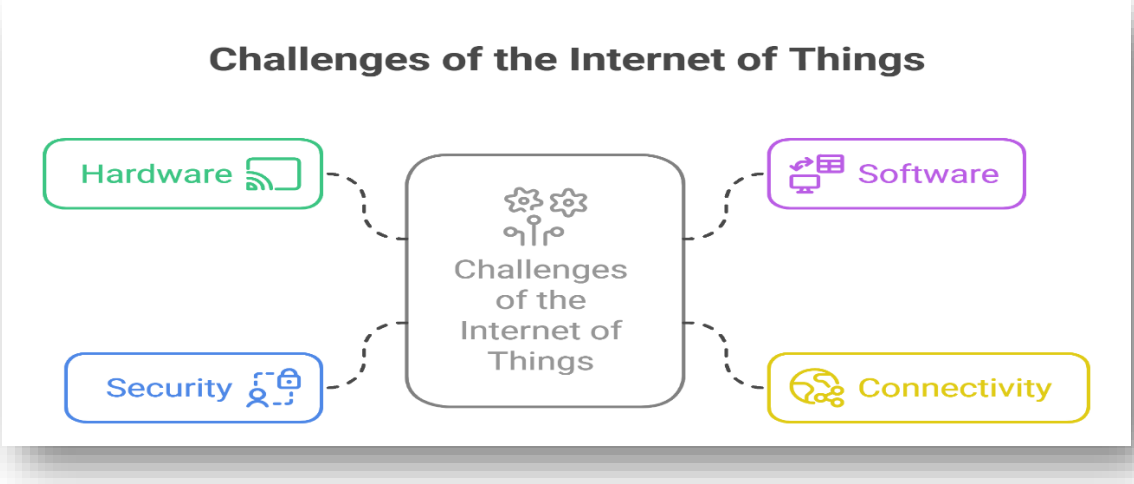

Figure 3: The Challenges of the Internet of Things

I.6.1 Hardware:

The number of Internet-connected devices grows exponentially leading to the following issues:

Cost of devices:

IoT devices have to be extremely low cost in some specific use cases, otherwise, the added value will not be able to justify the cost.

Battery life:

Most of the IoT devices will be battery powered and, in some cases, powered by unpredictable renewable energy sources. Therefore, the devices should be working as long as possible.

Physical specifications:

There is certainly a big pressure on the overall size of devices while maintaining or even increasing their computing power. **[12]**

I.6.2 Software:

No IoT solution would work without a sufficient software. The software used to date does not meet the emerging IoT requirements, motivating new developments. To meet the continuously increasing demands, new software solutions need to be targeted at:

Interoperability:

The IoT not only connects things to the Internet, but it also interconnects things in a meaningful way to enable a mutual machine-to-machine (M2M) communication. This approach requires a globally accepted standardization, which has been a motivation for many organizations to take the initiative.

Data processing:

The IoT continues to generate increasingly more data as more devices are connected. Decentralized data processing is inevitable with much of it done as close to the data sources as possible.

Context awareness:

To fulfil the idea of controlling an environment without human interaction, the artificial intelligence has to be implemented to provide context aware computing. **[12]**

I.6.3 Connectivity:

Coverage:

Extended coverage is needed both in indoor spaces and wide outdoor areas **[13]**. A combination of both multi-hop short-range as well as one-hop long-range technologies would be essential.

Scalability and diversity:

Networks have to scale efficiently and rapidly to meet the increasing demands of up to millions of connected devices. Furthermore, the diversity of connection scenarios requires the network to be able to adapt to different traffic requirements.

Reliability:

IoT is the foundation of cyber-physical systems (CPS) that we have become more and more reliant on. Consequently, network reliability is a critical requirement, much more than the best-effort service model that original Internet was designed for. **[12]**

I.6.4 Security:

Being a cyber-physical system, it has been acknowledged that its vulnerability to attacks can lead to costly or even life-threatening consequences. another side of the IoT security problem has emerged where a massive number of IoT devices is easily exploited to execute malicious activities, namely, distributed denial-of-service (DDoS) attacks **[14]**. This implies that IoT solutions need to offer:

Attack resistance:

Since resource-constrained IoT de vices need to be resistant to attacks as well as from being used as attack vectors, security measures must be an integral component of every IoT device's protocol stack.

Confidentiality, integrity, and availability:

Since both information and device require different measures that impose different requirements on the resource constrained IoT devices, the appropriate choice of measure(s) is crucial to balance the needs against the available resources.**[12]**

I.7 Applications of the Internet of Things:

With new wireless networks, revolutionary computing capabilities, and superior sensors, the IoT is expected to lead the competition. It has several applications in daily life, improving decision-making, reducing costs, and enhancing overall quality of life by leveraging real-time data and automation. Common applications of IoT devices include:

Smart homes for automation and energy efficiency, wearable health trackers for continuous monitoring, smart cities for traffic and resource management, and connected vehicles for enhanced safety and navigation. As IoT continues to evolve, its integration across sectors promises to reshape the way we live and work by offering greater control, efficiency, and connectivity.**[15]**

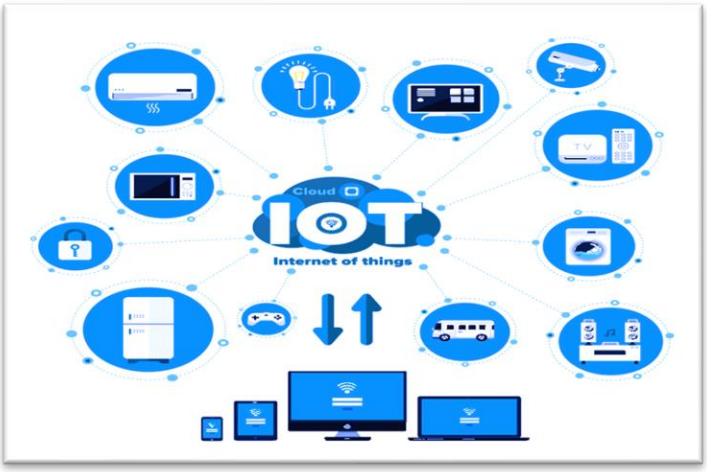

Figure 4: Applications of the Internet of Things

I.7.1 Smart home:

It is made possible by IoT devices and automation of control of HVAC, lighting, security and appliances in homes, which improve comfort and well-being.

I.7.2 Smart city:

IoT technologies are used to optimize urban infrastructure and services, such as waste management, public safety, energy and transportation systems, and environmental monitoring, improving the quality of life for locals and promoting sustainability.**[16]**

I.7.3 Health connected:

Household medical devices like sphygmomanometer are access to the network of IOT and community hospital. So doctors can keep in touch with the patients' health condition conveniently and make timely treatment.**[17]**

I.7.4 Vehicles:

Vehicles connected to the internet allows users to access data to the cars maintenance and it can enable the ability to electronically pay tolls.**[18]**

I.7.5 Transportation:

IoT has its contribution in transportation, IoT can assist in the integration of communication, control, and information processing across various transportation systems. IoT extends in all field of transportation, like smart parking of vehicles, smart traffic, electronic toll collection, vehicle control in emergency time, and road assistance.

I.7.6 Agriculture:

There are many types of IoT sensors for agriculture as well as IoT has numerous applications in farming that help a farmer to produce a better productivity of crops here IoT Devices collects data of climate, humidity, pest infestation, and soil content and it is used to automate farming techniques for crop management, by this farmer can improve quantity and quality, and there will be minimization of risk and waste and reduce the effort required to crop management.**[40]**

I.8 Conclusion:

Chapter 1 provides an extensive overview of the Internet of Things (IoT), covering its fundamental definition, architectural layers, resource limitation, critical elements, and the Challenges of it . It serves as a comprehensive introduction to the subject, offering insights into its complexities and practical applications. In the next chapter, we will discuss the security of the Internet of Things and present its most important security vulnerabilities and the attacks that it may face.

Chapter 2:

Malware and Security Mechanisms In IoT

II. Chapter 2: Malware and Security Mechanisms In IoT

II.1 Introduction:

IoT malware is a type of malicious software or code that targets Internet of Things (IoT) devices, which are increasingly common in homes, businesses, and industrial settings. IOT Malware can cause a range of harmful effects, such as stealing sensitive data, disrupting device functions, or even causing physical harm. As the number of connected devices grows, so does the risk of IoT malware attacks. To protect against such threats, specialized security controls and technologies are needed, such as firewalls, intrusion detection systems, and antivirus software. Additionally, best practices for IoT security, such as regular software updates, strong passwords, and network segmentation, can also help prevent and mitigate the effects of IoT malware.**[19]**

II.2 Internet Of Things Attack Types:

Attacks on IoT (Internet of Things) devices are diverse due to the wide range of devices, protocols, and applications involved. IoT attacks can be divided into six sections based on domain: physical attacks, network attacks, software attacks, encryption attacks, data attacks, and side channel attacks.**[30]**

II.2.1 Physical attacks:

Attackers tamper with hardware to extract data or bypass security, Physical attacks can be launched if the attacker remains physically close to the network or devices of the system**[31]**. New IoT vulnerabilities are frequently found through physical attacks. The attacker will attempt to physically access the device before launching the attack by purchasing a duplicate of the targeted IoT device from the market. They would then develop a false attack “test” using reverse engineering to determine what kind of outputs might be acquired from it. These physical attacks expose the system's vulnerabilities **[32]**. Examples include:
Tampering, Fault Injection, RF Spoofing/Jamming, Fake Node Injection, Social Engineering, Sleep Denial Attack, Permanent Denial of Service (PDoS), Malicious Code Injection.

II.2.2 Network attacks :

IoT devices use the network layer to send data to a server or other devices for processing after receiving it from the physical layer. To damage IoT network systems, network attacks are carried out by manipulating them. Without being near the network, it may be deployed with ease.

Network attacks are a subset of cyberattacks that target the communication infrastructure of IoT devices. **[33,30]** Some of the network attacks are:

RFID Spoofing, *RFID Unauthorized Access*, *Routing Attacks/Routing Information Attacks*, *Man-in-the-middle Attack (MiTM)*, *Replay Attack*, *Denial/Distributed Denial of Service (DoS/DDoS) Attack*, *Hello-flooding* ,*Clone (Node-replication)*, *Routing Diversion/Misdirection Attacks*, *Routing Loop Attacks*, *Rushing Attacks*, *RPL Exploit*, *DNS Attacks*, *Network Eavesdropping or Sniffing*, *Zero-day*.

II.2.3 Software/application attacks:

IoT (Internet of Things) software attacks involve exploiting vulnerabilities in IoT devices, systems, or network software components to compromise security, steal data, disrupt operations, or gain unwanted access. These attacks are directed at the software layer of IoT devices, which includes their operating systems, applications, firmware, and any software interfaces with which they communicate.**[11]** Some of the software attacks are:

Malware Attacks: Malware is malicious software designed to exploit or attack devices through their hardware or software. Malware is classified into several types: viruses, Trojans, rootkits, backdoors, etc.
Code Injection, *Remote Code Execution*, *Buffer Overflow*, *Vulnerable Firmware*, *Man-in-the-middle (MitM) Attacks*, *Zero-day Exploits*, *Authentication Attacks*, *Phishing Attacks*, *Reverse, Engineering Attacks*, *Sniffing Attacks*, *Logic Bombs*, *Exploitation of a Misconfiguration*, *Cross-site Scripting*.

II.2.4 Encryption *a*ttacks:

IoT security threats may include attacks on encryption schemes. Side-channel attacks target the implementation of cryptographic methods rather than the algorithms themselves. By analyzing physical signals generated during computation and the internal state of the device during processing, attackers may be able to extract the encryption key **[34]**.

II.2.5 Data attacks:

The term “data attack” in the context of the IoT refers to a variety of malicious actions intended to jeopardize the availability, confidentiality, integrity, and general security of data inside IoT systems. The IoT is a network of interconnected smart devices that gather, share, and analyze data, making them vulnerable to various data-related attacks.**[30]** Some common data attacks in IoT include:

Data Interception and Eavesdropping, *Data Tampering*, *Replay Attacks*, *Man-in-the-middle (MitM) Attacks*, *Denial of Service (DoS) and Distributed Denial of Service (DDoS) Attacks*, *Data Falsification*, *Device Impersonation*, *Firmware and Software Exploitation*, *Insecure APIs and Interfaces*.

II.2.6 Side channel attacks:

Side channel attacks are a class of attacks that exploit "side channel information", which refers to information that may be obtained from encryption devices other than the plaintext or the ciphertext produced by the encryption process. Encryption devices provide quantifiable time information, statistics on power usage, and several other data. Instances of side channel information include temporal attacks, power analysis attacks, interference analysis attacks, electromagnetic attacks, and environmental attacks.

II.3 Security Vulnerabilities In IoT:

Significant vulnerabilities exist in IoT systems' software, hardware, networks, and chips. Adversaries can gain control through software weaknesses, including weak authentication and vulnerable firmware. Man-in-the-middle attacks on sensors and Advanced Metering.
Infrastructure (AMI) are two examples of hardware vulnerabilities that can result in data theft and grid disruption.
Inadequate security measures cause network vulnerabilities, as demonstrated by breaches in devices such as Amazon's Ring owing to unencrypted protocols. Chip vulnerabilities include Hardware Trojans (HTs) and side-channel attacks, which allow adversaries to obtain cryptographic keys and sensitive data, posing serious security risks**.[25]**

Here are some common vulnerabilities:

1. **Password-Based Authentication:** Many IoT devices use default or weak passwords, making them vulnerable to brute-force attacks.**[26]**

2. **Inadequate Firmware Updates:** The absence of robust firmware update procedures in IoT systems exacerbates security vulnerabilities, leaving devices susceptible to exploitation and undermining the integrity of the entire network.**[27]**

3. **Privacy Concerns:** Sensitive data is collected and processed by IoT devices, giving rise to privacy issues with data collecting, storage, and sharing procedures.
   Insufficient safeguards against data loss could leave private or sensitive data vulnerable to illegal access or disclosure.**[28]**

4. **Network Reconnaissance:** To obtain strategic intelligence, attackers make use of their comprehension of the network topology. They can locate vital infrastructure components, identify possible targets, and create complex attack methods by examining the network configuration. With this knowledge, they may optimize the impact of their activities and successfully exploit weaknesses.**[29]**

II.4 Definition of Malware:

In the context of computer security the malware is: **"** short for malicious software, refers to any intrusive software developed by cybercriminals (often called hackers) to steal data and damage or destroy computers and computer systems**"**. Examples of common malware include viruses, worms, Trojan viruses, spyware, adware, and ransomware. Recent malware attacks have exfiltrated data in mass amounts. **[20]**

II.5 Types of Malware:

Malware classification is a sub-field in cybersecurity, where in light of the continuous evolution of malware, understanding these classifications is very important, in order to help cybersecurity consultants develop their strategies, and to simplify the task of recognizing, diagnosing and solving malware-related threats.
Malware has been divided by researchers into several classifications based on:

- How it is introduced into the system
- The type of breach it aims to cause
- Behavior
- Propagation method

The most common classifications of malware:

Virus:

Malware which spreads from one computer to another by embedding copies of itself into files, The virus need a host to spreading he doesn't work by itself. the virus is difficult to remove and attacks the device in a complicated way. Silex, for example, is an IoT virus that enters the device and bricks it, commonly known as a permanent DoS attack.**[21]**

Worm:

Malware which spreads from one computer to another by transmitting copies of itself via a network which connects the computers without used the infected files, Juniper Threat classifies the worm as annoying malware due to its propagation mode. Mirai, Darlloz, Brickerbot, and Gitpaste-12 are some of the worms in IoT devices.**[21]**

Trojan Horse:

A Trojan, often known as a Trojan horse or Trojan virus, is another type of IoT malware that seems innocent to users despite having hidden malicious functionality. Indeed, the functionality of a Virus and a Trojan is completely different because the Trojan cannot replicate itself, but the Virus can. ProxyM , for example is an IoT virus that does email spamming and attacks involving DDoS.**[22]**

Ransomware:

Is malware that encrypts or locks a victim's data and demands payment to unlock it .Once infected, the attacker encrypts the data and prevents users from viewing it. The attacker delivers the decryption key and releases the device after receiving the ransom. Necurs is an IoT virus that performs ransomware attacks and other forms of digital extortion.**[22]**

Spyware:

Is malware that secretly monitors and collects a user's data without their consent. It can capture passwords, browsing habits, or personal information and send it to attackers. Spybot, Skeeyah, and HNS are examples of IoT spyware that monitors users. As the use of IoT devices grows, so does the number of attacks perpetrated by this malware.

Backdoors:

Are hidden entry points in software or devices that allow attackers to bypass normal security controls. They enable unauthorized access to systems, often without the user's knowledge. backdoors are also known as the front doors of attackers. Tsunami and Bashlite are backdoor IoT malware with a few resources that address them as Trojans.

Adware:

It is a type of software that automatically displays or downloads advertising material when a user is online. It often comes bundled with free programs and can track user behavior to serve targeted ads. Common examples include Fireball and HummingBad, which inject ads, hijack browsers, and collect user data. Many resources classify them under potentially unwanted programs (PUPs) or mobile adware trojans.

Botnet:

Botnets are networks of compromised devices—called bots—that are remotely controlled by an attacker, usually without the device owner's knowledge. They are used to carry out coordinated malicious activities such as DDoS attacks, credential stuffing, spam campaigns, and data theft. Botnets are also known as the zombie armies of cyber attackers. Common IoT botnet examples include Mirai and Mozi, which infect smart devices with weak credentials and turn them into attack tools. Many resources categorize botnets under command-and-control (C2) malware or distributed attack platforms.

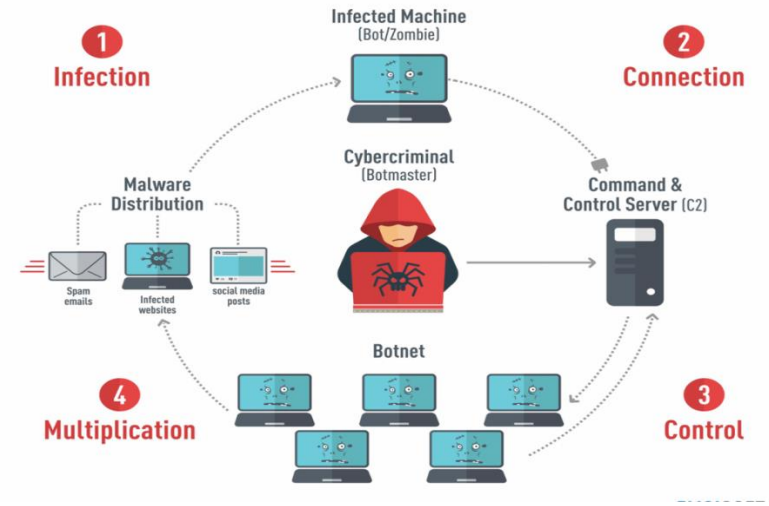

Figure 5: Botnet Process

Types of IoT botnet:

Numerous botnets are currently in operation. Some of the most significant include:

- **Mirai:** Mirai is an IoT botnet that spreads by logging into devices using default credentials. It spawned many new botnets after its source code was made public.**[23]**
- **Mozi:** First detected in 2019, Mozi bears most of the modern features in the IoT environment. It infects devices using a hard-coded list of common credentials and specific vulnerabilities. It uses the DHT protocol to download and verify a config file.**[24]**
- **Qbot:** Qbot is an IoT botnet that first emerged in 2008 but is still active today. Like many other botnets, Qbot includes code to remove other botnet malware from an infected device.

- **Kaiten:** Kaiten's codebase has been open-source since 2001, enabling many less-skilled criminals to operate botnets. Kaiten spreads by brute-forcing passwords to Telnet.
- **Reaper:** Reaper — also known as IoTroop — is a botnet that was first discovered in 2017. This botnet malware spreads by exploiting known vulnerabilities in a range of devices. **[23]**

II.6 Malware Detection Methods in Internet Of Things:

II.6.1 Using Machine Learning Classifier:

Many methods for detecting IoT malware using machine learning techniques. Static analysis, dynamic analysis and hybrid analysis, those are the three types of Internet Of Things malware detection methods. **[35]**

Static Analysis:

Static analysis is the extraction of data from a malware that is at rest. It is a low-cost method of detecting malware. We have discussed recent IoT and android malware detection and classification methods based on static features like control flow graph (CFG), file header, operation code (opcode), strings with various machine learning classifiers such as support vector machine (SVM), decision tree, random forest (RF), K-nearest neighbor (KNN), Naive Bayes, etc. This technique will not detect malware that employs code obfuscation.

Dynamic Analysis:

Dynamic analysis is used to observe real-time behavior of the application to discover malicious patterns. Dynamic analysis is the process of evaluating a sample by executing it in a controlled environment and monitoring its activities, interactions and impact on the system. System calls and API calls analysis and control flow analysis are the main methods used for dynamic analysis. Dynamic monitoring tools like Process Hacker and Process Monitor are used for inspecting process attributes and system interaction. Wireshark is used to capture network traffic. However, dynamic analysis is time consuming and resource intensive.**[35]**

Hybrid Analysis:

Hybrid analysis incorporates both static analysis and dynamic analysis. It overcomes the limitations of both static and dynamic analysis. It explores by examining malware code’s signature and continue by combining it with other behavioral pattern factors to improve malware analysis, although this approach is much time consuming and costly.

II.6.2 Using Deep Learning Classifiers for IoT Malware Detection:

Deep learning (DL) has emerged as a powerful approach for detecting malware in Internet of Things (IoT) environments, offering enhanced accuracy and adaptability compared to traditional machine learning techniques. DL-based malware detection methods are typically categorized into three analytical approaches: static analysis, dynamic analysis, and hybrid analysis.

Static Analysis:

Static analysis involves examining malware without executing it, focusing on extracting features from the code at rest. In the context of deep learning, static features such as control flow graphs (CFGs), bytecode sequences, file headers, and opcodes are transformed into structured inputs like sequences or images. These inputs are then processed by deep learning models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformers. This method is efficient and scalable, making it suitable for large datasets. However, it may struggle to detect sophisticated malware that employs code obfuscation or encryption techniques.**[36]**

Dynamic Analysis:

The major role of dynamic analysis is observe the behavior of malware during execution mode. Dynamic analysis examines the behavior & activities taken by the application when it is running to determine whether itis infection or not. In deep learning-based dynamic analysis, features such as API call sequences, system call traces, and network behavior are collected and analyzed using models like Long Short-Term Memory (LSTM) networks or hybrid CNN-LSTM architectures. These models are capable of identifying temporal patterns and behavioral anomalies that static analysis may miss. While dynamic analysis offers improved detection of evasive malware, it is computationally intensive and requires significant resources.**[37]**

Hybrid Analysis:

The increasing harmful impacts on every upcoming technology, motivates the researchers to face open challenges in malware detection,[34] classification and its prevention to ensure the security parameters. the Hybrid analysis combines both static and dynamic analysis, leveraging the strengths of each to achieve more comprehensive detection. Deep learning approaches in hybrid analysis typically use multi-modal architectures that ingest both static code features and dynamic behavior logs. This fusion allows models to better understand the full context of malware activity. Although hybrid deep learning models tend to be more accurate and robust, they also require greater computational resources and longer processing times.

II.6.3 Using Blockchain Technology:

Blockchain technology, as a distributed network, enables secure communication between devices, reducing the risk of cyber threats. The internet layer, ledger layer, and application layer are all measures for detecting malware in IoT devices using blockchain. Blockchain facilitates IoT security needs by identifying malicious actors and maintaining tamper-resistant records **[38]**. The most effective way to use IoT with blockchain is to install chips in sensors and devices used in a specific IoT system.

II.6.4 Using Convolutional Neural Network (CNN):

Convolutional Neural Networks (CNNs) are among the most effective machine learning techniques for detecting malware in IoT and Android systems. They possess the capability to uncover malicious code concealed within seemingly benign applications, thereby minimizing the risk of detection failures. In graphical-based analysis, CNNs outperform other methods by transforming binary malware files into 8-bit vectors, which are then converted into images. These images serve as input for the CNN-based predictive model, enabling accurate and efficient malware detection.**[39]**

II.6.5 Using Federated Learning:

Federated Learning (FL) is a distributed machine learning approach that enables multiple IoT and edge devices to collaboratively train a shared global model while keeping the raw data localized. Instead of sending sensitive or high-volume data to a central server, only model updates (such as gradients or parameters) are exchanged between devices and the cloud. This preserves data privacy, reduces communication overhead, and enables decentralized intelligence across large-scale, heterogeneous IoT networks in industrial and automation contexts.**[40]**

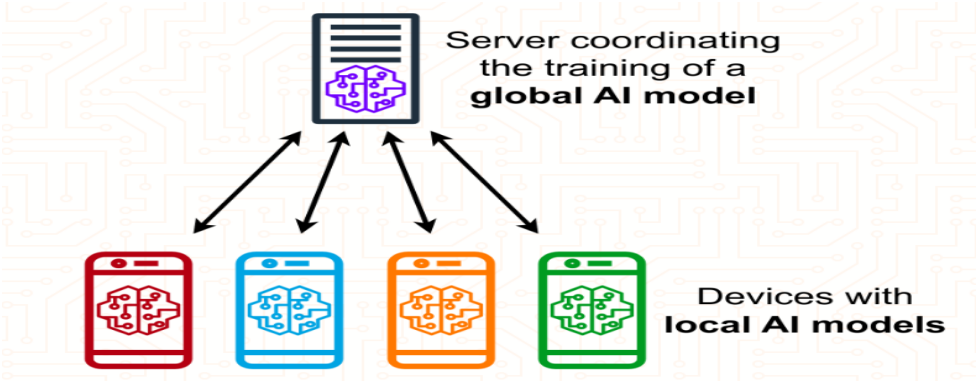

Figure 6: Federated Learning

II.6.6 Using Behavior-Based Detection:

Behavior-based Detection focuses on analyzing the behavior of files and processes to identify potential threats based on deviations from normal patterns of operation. By monitoring system activities and analyzing behavioral anomalies, this approach can detect previously unknown malware variants.

This method of threat detection differs from traditional signature-based approaches that rely on known malware signatures. Behavior-based detection is more proactive, as it doesn't require prior knowledge of specific threats. It excels in detecting polymorphic and zero-day malware that can evade signature-based defenses. The key advantage of behavior-driven analysis lies in its ability to identify advanced threats that may not yet have known signatures, making it crucial for staying ahead of cyber attacks.

This method is particularly effective in the Internet of Things (IoT) environment, where devices often have limited resources and may be vulnerable to novel or sophisticated attacks.**[41]**

II.6.7 Using Signature-based Detection:

Signature-based Detection is a method used by traditional anti-malware tools to identify known malware signatures by comparing suspicious files or behavior with a database of predefined signatures. When a match is found, the system flags the file as malicious and initiates appropriate actions.

This approach relies heavily on recognizing fixed, unchanging patterns associated with malware. While effective in detecting well-known threats, signature-based detection struggles with polymorphic and metamorphic malware that constantly alter their code to evade detection. Polymorphic malware changes its appearance each time it infects a new system, generating unique variants that may not match existing signatures. Similarly, metamorphic malware modifies its entire structure, making it difficult for traditional signature-based tools to keep up. This limitation highlights the need for complementary detection methods that can adapt to evolving threats.**[41]**

II.7 Conclusion:

This chapter is dedicated to overview of malware the security of the IoT network, where we talked about the malware and it's types, its mechanisms, and the vulnerabilities and the attacks carried out by attackers in the IoT devices, with mentioning detecting methods for attacks.

In the next chapter, we will talk about the random forest, how it works, and present the implementation results.

CHAPTER 3:

Proposed System and Result

III. Chapter 3: Proposed System and Result

III.1 Introduction:

The rapid expansion of Internet of Things devices has led to an increase in security vulnerabilities, particularly in the form of botnet attacks.
Botnets is a network of compromised or infected Internet of Things devices that can be remotely controlled by cybercriminals for malicious purposes such as distributed denial of service (DDoS) attacks, spreading malware, stealing data, and engaging in other types of cyberattacks.[4]
The Mirai botnet and the gafgyt botnet are among the most common botnet attacks targeting IoT devices. These attacks exploit security vulnerabilities in IoT devices, leading to their infiltration and transformation into an army of bots that can be used in various types of attacks.

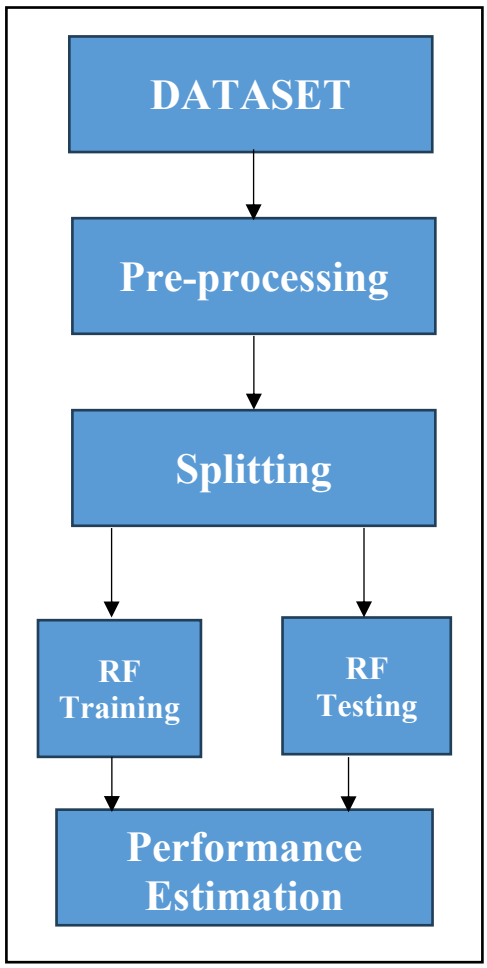

Figure 7: Diagram of proposed System

III.1.1 Data Pre-processing:

Data pre-processing is the process of Preparing, cleaning, and modifying the data so that it is ready to feed the machine learning model correctly and without problems. This is the first and most important step in creating a machine learning model.

Why do we need data pre-processing?

Real-world data often contains outliers, missing data, and noise, making it unusable and unsuitable for direct use in machine learning models. Data preparation and processing is a necessary step to make it suitable for machine learning models, ensuring the quality, accuracy, and efficiency of the machine learning model.

III.1.2 Data preparing steps:

Data Cleaning:

Delete rows or columns that contain:

- Missing values (NaN)
- Outliers
- Processing missing data

Feature Selection:

- Remove useless or duplicate columns.
- Retain only features that may help detect malware.

Label Encoding:

Converting text data into numeric data that the model can process.
For example: Benign -> 0 , Malware -> 1.
Feature Scaling.

III.1.3 Splitting dataset into training and test set:

This step is crucial in data preprocessing, as it allows us to improve the performance of the machine learning model.
After the data processing process, the model is not trained on the entire data directly, but rather split into two parts. But why split it into two parts?
The data is split into two parts for several main reasons:
To avoid the problem of overfitting, which causes the model to memorize the training data verbatim without learning the general patterns. This is to ensure that the model learns correctly.
To avoid the problem of underfitting, which is the model's inability to learn the underlying patterns in the training data, leading to poor performance on both the training and test data.
Also, one of the most important goals when building a machine learning model is to simulate how the model will perform.

In reality, when the model is deployed to Internet of Things (IoT) devices, it will encounter a constant influx of new data that it did not see during training. Therefore, it is essential to test the model's performance using an independent dataset that it has not been exposed to before during the learning phase.
This approach simulates a real-world scenario where future data differs from the training data. If the model performs well on the test set, it is a strong indicator that the model will be effective in practical applications, enhancing its reliability and validity when detecting real-world malware in IoT devices.

Training set: A subset from Dataset we use it to train the machine learning model**.**
Test set: A subset from Dataset we use it to train the machine learning model , when we using the test set the model predict the output.

III.2 Random Forest:

III.2.1 Definition:

Random Forest is one of the most popular and powerful machine learning algorithms, used for both classification and regression tasks. It is *an **ensemble learning method*** that builds multiple decision trees and combines their predictions to improve accuracy and reduce overfitting.

So, What is a Random Forest? But before talking about the random forest, we will give an overview of Ensemble learning method!

Ensemble learning method:

Is a machine learning technique, which makes predictions based on the different numbers of models . The goal of ensemble learning is to combine the predictions made by several estimators built using a particular algorithm so that it can produce better and more effective results .

There are 2 families of ensemble methods are usually distinguished:

A **random forest** is essentially a collection (or “forest”) of **decision trees** trained on different subsets of the data. Each tree in the forest is trained independently, and the final prediction is made by aggregating the predictions of all trees, either by taking the **majority vote** in classification or **averaging** the predictions in regression.
The core idea behind random forests is to combine multiple models to produce a more robust and accurate final model. This process helps mitigate the tendency of individual decision trees to overfit the training data.

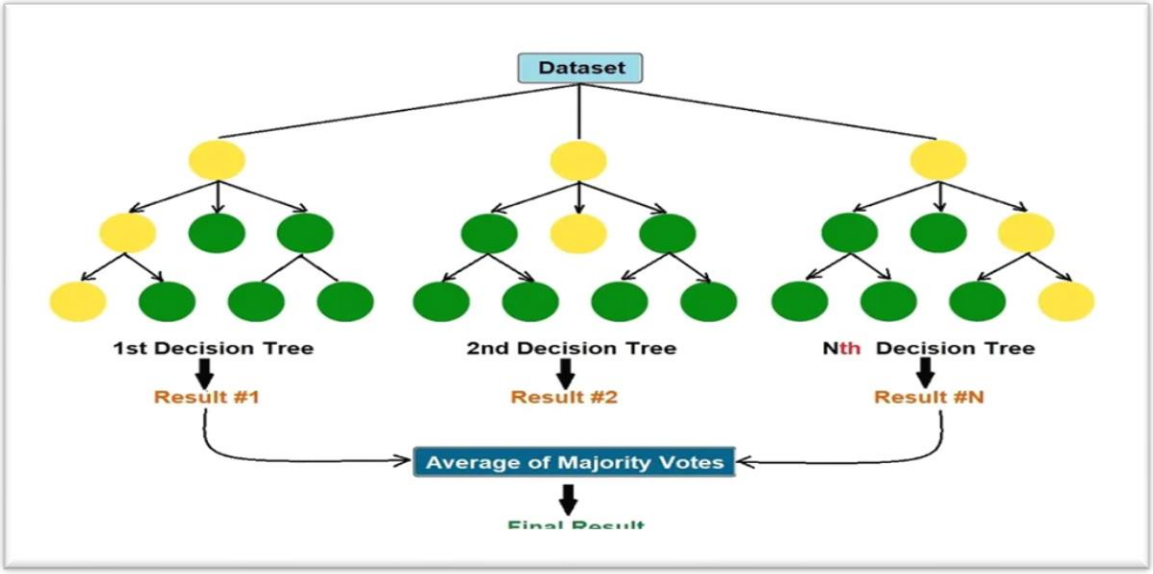

Figure 8: Splitting dataset

III.2.2 How Random Forest Works:

1. **Bootstrap Sampling (Bagging):**

From the original training dataset, multiple bootstrap samples are generated. A **bootstrap sample** is a random sample drawn **with replacement**, meaning that the same data point may appear more than once in a sample, while others may not appear at all.

Each decision tree in the random forest is trained on a different bootstrap sample.

2. **Random Feature Selection:**

At each node of the decision tree, instead of considering all features (as in standard decision trees), the algorithm randomly selects a subset of features. This adds additional randomness and helps decorrelate the trees, making the final model more generalizable.
This random feature selection is a key difference between random forests and bagging with decision trees.

3. **Aggregation:**

For classification, the predictions of all trees are combined using majority voting. The class that gets the most votes becomes the final prediction.

For regression, the predictions of all trees are averaged to produce the final output.

III.2.3 Gini Index:

As we said before, Random forest is a collection of decision tress , Those **Decision trees** are often used while implementing **machine learning algorithms**. The hierarchical structure of a decision tree leads us to the final outcome by traversing through the nodes of the tree. In simple, the 'knowledge' learned by a decision tree through training is directly formulated into a hierarchical structure. This structure holds and displays the knowledge in such a way that it can easily be understood, even by non-experts.

Each node consists of an attribute or feature which is further split into more nodes as we move down the tree. But how do we decide:

- Which attribute/feature should be placed at the root node?
- Which features will act as internal nodes or leaf nodes?

To decide this, and how to split the tree, we use splitting measures like Gini Index, Information Gain, etc. [2]

In our case we use Gini Index, so what is Gini Index and why we use Gini index?

Definition:

Gini Index OR **Gini impurity** is a measure used in decision tree algorithms to quantify a dataset's impurity level or disorder. In binary classification problems, it assesses the likelihood of an incorrect classification when a randomly selected data point is assigned a class label based on the distribution of classes in a particular node. It ranges from 0 to 0.5, where 0 indicates a perfectly pure node (all instances belong to the same class), and 0.5 signifies maximum impurity (an equal distribution of classes). In decision trees, it aids in selecting the optimal split by identifying features that result in more homogeneous subsets of data, ultimately contributing to the creation of accurate and reliable predictive models.[3]

The Formula for Gini Index:

$$Gini = 1 - \sum_{i=1}^{j} P(\mathrm{i})^2$$

Equation 1: The Formula of Gini index

Why we use Gini index:

We use Gini index in our project Because:

- Fast
- Accurate
- Suitable for imbalanced classes
- Powerful for complex data scenarios (such as IoT)

III.2.4 Key Hyperparameters of Random Forests:

Tuning the hyperparameters of a random forest model can have a significant impact on its performance. The main hyperparameters include:

1. Number of Trees (n_estimators):

This parameter specifies how many trees the random forest should include. More trees generally improve accuracy, but they also increase computational cost.

2. Number of Features to Consider (max_features):

•Controls how many features the algorithm should consider when making splits at each node. Options include:
•"auto": Use the square root of the number of features (default for classification).
•"sqrt": Same as "auto".
•"log2": Use the logarithm of the number of features.
•An integer: Specify an exact number of features to consider.

3. Tree Depth (max_depth):

Limits the maximum depth of the individual trees. Shallow trees help reduce overfitting, but if trees are too shallow, the model may underfit.

4. Minimum Samples per Split (min_samples_split):

The minimum number of samples required to split an internal node. Higher values prevent trees from being too specific to small groups of data, reducing overfitting.

5. Minimum Samples per Leaf (min_samples_leaf):

The minimum number of samples required to be at a leaf node. It prevents overly small leaves, which can lead to overfitting.

6. Bootstrap Sampling (bootstrap):

A Boolean parameter that controls whether bootstrap samples are used when building trees. If set to False, the entire dataset is used for training each tree.

III.2.5 Advantage of Random Forest:

- Random Forest provides very accurate predictions even with large datasets.
- Random Forest can handle missing data well without compromising with accuracy.
- It doesn't require normalization or standardization on dataset.
- When we combine multiple decision trees it reduces the risk of overfitting of the model.

III.3 Result And Discussion:

There is the results that we got it , But before presenting it, we will talk about an important idea that we used to ensure that the model learns correctly and that it does not fall into the problem of overfitting, which is **random labeling**.

Random Labeling: It is a technique used to test a machine learning model's ability to learn effectively, by replacing the original labels in the training data with completely random labels, and then training the model on this distorted data.**[41]**

If the results of training the model on the distorted data are the same as those obtained using the original data, this indicates that the model is not learning correctly.

If the training results on the distorted data are less than 50%, this indicates that the model is learning correctly. In other words, the model, in its original state, was learning real patterns in the data, not just memorizing them blindly.

III.3.1 Classification Explanation:

True Positive (TP) = Packets are benign and are predicted benign.

False Positive (FP) = Packets are malicious but predicted benign

True Negative (TN) = Packets are malicious and are predicted malicious.

False Negative (FN) = Packets are benign and are predicted malicious

Accuracy:

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FN + FP)}$$

Precision:

It measures the accuracy of positive predictions. That is, of all the samples the model predicted as "malicious," how many were actually malicious? If the value is high, it means few false alarms.

$$Bening = \frac{TN}{(TN+FN)}$$

$$Malware = \frac{TP}{(TP+FP)}$$

So, Let's Represent Those Results:

The random tree algorithm was applied with two data groups:
The first group “Usw_2018_iot_botnet_final_10_best”, which includes malware (3 sub - categories), as is the case for the second group “Baiot: provision_pt_838_secture_camera” , includes 4 categories, one healthy and three pure (without (without Capacity).

These are the results:

	Usw_2018_iot_botnet_final_10_best	Baiot: provision_pt_838_secture_camera
Accuracy	**0.99**	**0.99**
Prediction time	**0.2330 Seconds**	**0.0481 Seconds**
Accuracy for random label	**0.55**	**0.36**

Table 1 : The Result

Confusion Matrix:

Baiot: provision_pt_838_secture_camera

predict / actual data	0	1	2	3
0	11662	0	0	0
1	0	3843	1	0
2	0	0	7812	0
3	1	0	0	10798

Table 2: Confusion Matrix dataset 1

Usw_2018_iot_botnet_final_10_best :

predict / actual data	1	2	3
1	264	3	0
2	0	158631	1
3	0	2	198813

Table 3: Confusion Matrix dataset 2

Discussion :

Through the results presented, the model proved its efficiency based on several things: He gave a 99 % high accuracy of the two data groups, and has proven that it can avoid getting involved, by experimenting with the random mark, which also fell significantly, and this proves that the model is learning in an appropriate way.
Also for an excellent prediction time for both cases.
Also, due to the advantages of this algorithm, we can control hyperparameter, so that we can make them agree with the limited Internet resources.
The model also showed its ability to deal with very large data, because USW_2018_iot_botnet_final_10_Best is huge compared to the Baiot data, and this indicates the ability of the algorithm to deal with data in real time, as IOT devices are very huge data, however the model can predict an excellent time.

We could not achieve this unprecedented accuracy and excellent speed if it was not for the unique characteristics of the random forest in dealing with complications from the Internet of Things data, which makes it a logical choice, to meet the project requirements, which is a light algorithm application to detect harmful programs in Internet devices, taking into account limited resources.

III.4 Conclusion:

Finally, we successfully completed our project. During our study, we extensively discussed our working environment, explained the structure of our proposed project, and provided a detailed overview of the stages we went through to obtain our project results.

General Conclusion

The Internet of Things (IoT) has grown rapidly as more and more devices become connected in various areas of our lives. However, this expansion has also brought about an increase in security vulnerabilities, specifically through botnet attacks. Botnets are networks of compromised devices that are controlled by malicious individuals. These attackers can use these botnets to launch cyber-attacks on a large scale. Two well-known botnet attacks that target IoT devices are the Gafgyt and Mirai botnets. These attacks take advantage of security weaknesses in IoT devices, compromising them and using them as bots to carry out their malicious activities.

The number of Internet Of Things devices is continually growing, and they are becoming increasingly integrated into critical infrastructure and our everyday lives. The consequences of botnet attacks can be very serious, disrupting services, compromising sensitive data, and even posing physical risks. To address this challenge, it is important to develop effective methods to identify and mitigate IoT botnet attacks promptly. One promising approach is the use of the Random Forest Classifier, which is a machine learning algorithm known for its accuracy and robustness in classification tasks.

The Random Forest Classifier combines the predictions of multiple decision trees to accurately determine the class labels of input data. It has been widely used in various fields, including cybersecurity, due to its ability to handle complex and large datasets.

The findings of this research advocate for a proactive approach to IoT security. As the adoption of IoT continues to expand, so too must our efforts to fortify these Devices against emerging threats. Future research should focus on developing innovative security solutions tailored to the dynamic nature of IoT environments. By doing so, we can safeguard the immense potential of IoT, enabling it to drive progress and improve quality of life across the globe.

References

[1] Soumyalatha, Shruti G. Hegde. "Study of IoT: understanding IoT architecture, applications, issues and challenges." 1st International Conference on Innovations in Computing & Networking (ICICN16), CSE, RRCE. International Journal of Advanced Networking & Applications. Vol. 478. sn, 2016.

[2] https://www.mongodb.com/resources/basics/cloud-explained/iot-architecture

[3] Zahoor, Saniya, and Roohie Naaz Mir. "Resource management in pervasive Internet of Things: A survey." Journal of King Saud University-Computer and Information Sciences 33.8 (2021): 921-935.

[4] "Ubiquitous ID: Standards for Ubiquitous Computing and the Internet of Things | IEEE Journals & Magazine | IEEE Xplore." Accessed: May 28, 2024. [Online].

[5] T. K. Gannavaram V, U. M. Kandhikonda, R. Bejgam, S. B. Keshipeddi, and S. Sunkari, "A Brief Review on Internet of Things (IoT)," in 2021 International Conference on Computer Communication and Informatics (ICCCI), Jan. 2021, pp. 1–6. doi: 10.1109/ICCCI50826.2021.9451163

[6] A. Shivakrishna and K. M. Lakshman Rao, "v/c ratio based on road geometrical elements using IoT sensors based on artificial neural network modeling," Meas. Sens., vol. 33, p. 101109, Jun. 2024, doi: 10.1016/j.measen.2024.101109.

[7] A. F. da Silva, R. L. Ohta, M. N. dos Santos, and A. P. D. Binotto, "A Cloud-based Architecture for the Internet of Things targeting Industrial Devices Remote Monitoring and Control," IFAC-Pap., vol. 49, no. 30, pp. 108–113, Jan. 2016, doi: 10.1016/j.ifacol.2016.11.137.

[8] M. Burhan, R. A. Rehman, B. Khan, and B.-S. Kim, "IoT Elements, Layered Architectures and Security Issues: A Comprehensive Survey," Sensors, vol. 18, no. 9, Art. no. 9, Sep. 2018, doi: 10.3390/s18092796.

[9] IoT malware: An attribute-based taxonomy, detection mechanisms and challenges P. Victor, A.H. Lashkari, R. Lu, T. Sasi, P. Xiong, S. Iqbal

[10] Mocnej, Jozef, et al. Network traffic characteristics of the IoT application use cases. Wellington, New Zealand: School of Engineering and Computer Science, Victoria University of Wellington, 2018.

[11] "NB-IoT: A sustainable technology for connecting billions of devices," accessed: 31/10/2016. [Online].

[12] C. Rodriguez, "IoT Risk Becomes Real: DDoS Emerges as Primary Threat Vector for IoT," Stratecast Perspectives & Insight for Executives (SPIE), Frost & Sullivan, vol. 16, no. 41, 11 November 2016.

[13] U. Elordi, A. Bertelsen, L. Unzueta, N. Aranjuelo, J. Goenetxea, and I. Arganda-Carreras, "Optimal deployment of face recognition solutions in a heterogeneous IoT platform for

secure elderly care applications," Procedia Comput. Sci., vol. 192, pp. 3204–3213, Jan. 2021, doi: 10.1016/j.procs.2021.09.093.

[14] B. Li and J. Yu, "Research and Application on the Smart Home Based on Component Technologies and Internet of Things," Procedia Eng., vol. 15, pp. 2087–2092, Jan. 2011, doi: 10.1016/j.proeng.2011.08.390.

[15] H. Ziwei et al., "The applications of internet of things in smart healthcare sectors: a bibliometric and deep study," Heliyon, vol. 10, no. 3, p. e25392, Feb. 2024, doi: 10.1016/j.heliyon.2024.e25392.

[16] "HC3 TLP White Analyst Note: Internet of Things (IoT) Security - August 04, 2022 | AHA." Accessed: May 27, 2024. [Online].

[17] https://www.kudelski-iot.com/glossary/iot-malware#:~:text=IoT%20malware%20refers%20to%20malicious,devices%20or%20industrial%20control%20systems.

[18] https://www.cisco.com/site/us/en/learn/topics/security/what-is-malware.html#tabs-35d568e0ff-item-4bd7dc8124-tab

[19] Sasi, Tinshu, et al. "A comprehensive survey on IoT attacks: Taxonomy, detection mechanisms and challenges." Journal of Information and intelligence 2.6 (2024): 455-513.

[20] Victor, Princy, et al. "IoT malware: An attribute-based taxonomy, detection mechanisms and challenges." Peer-to-peer Networking and Applications 16.3 (2023): 1380-1431.

[21] IoT Botnet - Check Point Software

[22] IoT Botnet - Definition | Trend Micro (FI)

[23] R. Ramadan, "Internet of Things (IoT) Security Vulnerabilities: A Review," PLOMS AI, vol. 2, no. 1, 2022, Accessed: May 24, 2024. [Online].

[24] P. Singh and S. Sachdeva, "A Landscape of XML Data from Analytics Perspective," Procedia Comput. Sci., vol. 173, pp. 392–402, Jan. 2020, doi: 10.1016/j.procs.2020.06.046

[25] I. Nadir, H. Mahmood, and G. Asadullah, "A taxonomy of IoT firmware security and principal firmware analysis techniques," Int. J. Crit. Infrastruct. Prot., vol. 38, p. 100552, Sep. 2022, doi: 10.1016/j.ijcip.2022.100552.

[26] A. Bhardwaj, S. Bharany, A. W. Abulfaraj, A. Osman Ibrahim, and W. Nagmeldin, "Fortifying home IoT security: A framework for comprehensive examination of vulnerabilities and intrusion detection strategies for smart cities," Egypt. Inform. J., vol. 25, p. 100443, Mar. 2024, doi: 10.1016/j.eij.2024.100443.

[27] S. A. Shaikh, H. Chivers, P. Nobles, J. A. Clark, and H. Chen, "Network reconnaissance," Netw. Secur., vol. 2008, no. 11, pp. 12–16, Nov. 2008, doi: 10.1016/S1353-4858(08)70129-6.

[28] Sasi, Tinshu, et al. "A comprehensive survey on IoT attacks: Taxonomy, detection mechanisms and challenges." Journal of Information and intelligence 2.6 (2024): 455-513.

[29] J. Sengupta, S. Ruj, S. Das Bit A comprehensive survey on attacks, security issues and blockchain solutions for IoT and IIoT

[30] Woo, S. "The right security for IoT: physical attacks and how to counter them." Profit From IoT. http://www. iot. electronicsforu. com/headlines/the-right-security-for-iot-physical-attacks-and-how-to-counter-them/. Accessed 13 (2019).

[31] Proceedings of 2021 IEEE 11th Annual Computing and Communication Workshop and Conference (CCWC), IEEE, Piscataway (2021), pp. 853-859

[32] https://securityintelligence.com/a-primer-on-iot-security-risks/

[33] Kakati, Sangeeta, et al. "Survey on Recent Malware Detection Techniques for IoT." Pattern Recognition and Data Analysis with Applications. Singapore: Springer Nature Singapore, 2022. 647-659.

[34] Song, Yafei, et al. "Application of deep learning in malware detection: a review." Journal of Big Data 12.1 (2025): 99.

[35] Hussain, Syed Shuja, Mohd Faizal Ab Razak, and Ahmad Firdaus. "Deep Learning Based Hybrid Analysis of Malware Detection and Classification: A Recent Review." Journal of Cyber Security and Mobility (2024): 91-134.

[36] Yang, W., Aghasian, E., Garg, S., Herbert, D., Disiuta, L., Kang, B.: A survey on blockchain- based internet service architecture: requirements, challenges, trends, and future. IEEE Access 7, 75845–75872 (2019)

[37] Kakati, Sangeeta, et al. "Survey on Recent Malware Detection Techniques for IoT." Pattern Recognition and Data Analysis with Applications. Singapore: Springer Nature Singapore, 2022. 647-659.

[38] Savazzi, Stefano, et al. "Opportunities of federated learning in connected, cooperative, and automated industrial systems." IEEE Communications Magazine 59.2 (2021): 16-21.

[39] https://blog.securetrust.io/blog/advanced-malware-detection-techniques-for-various-sbusiness-environments

[40] Bhavana, B. C., CT Vathsala Gowda, and B. H. Rakshitha. "A Survey: Internet of Things (IOT) Technologies, Applications." *International Journal for Research in Applied Science and Engineering Technology* 10.8 (2022): 640-644.

[41] Zhang, Chiyuan, et al. "Understanding deep learning requires rethinking generalization." arXiv preprint arXiv:1611.03530 (2016).