A Survey on Consumer IoT Traffic: Security and Privacy

Yan Jia, Yuxin Song, Zihou Liu, Qingyin Tan, Fangming Wang, Yu Zhang, Zheli Liu

Abstract-For the past few years, the Consumer Internet of Things (CIoT) has entered public lives. While CIoT has improved the convenience of people's daily lives, it has also brought new security and privacy concerns. In this survey, we try to figure out what researchers can learn about the security and privacy of CIoT by traffic analysis, a popular method in the security community. From the security and privacy perspective, this survey seeks out the new characteristics in CIoT traffic analysis, the state-of-the-art progress in CIoT traffic analysis, and the challenges yet to be solved. We collected 310 papers from January 2018 to December 2023 related to CIoT traffic analysis from the security and privacy perspective and summarized the process of CIoT traffic analysis in which the new characteristics of CIoT are identified. Then, we detail existing works based on five application goals: device fingerprinting, user activity inference, malicious traffic analysis, security analysis, and measurement. At last, we discuss the new challenges and future research directions.

Index Terms—Consumer IoT, Traffic Analysis, Security, Privacy, Survey.

I. INTRODUCTION

Over the past few decades, an increasing number of industries related to the Internet of Things (IoT) have become part of people's lives, such as smart cities [1], smart cars [2], industrial automation [3], smart homes [4], and smart healthcare [5]. According to a report by IoT Analytics [6], the global IoT market is expected to grow by 21% in 2024, reaching \$287 billion.

Consumer Internet of Things (CIoT) has garnered increasing attention as many manufacturers enter this industry. However, the short production cycles and limited capabilities of CIoT devices render them incapable of defending against potential security risks, which allow attackers to intrude on target devices and compromise user privacy and personal information [7]. Consequently, researchers are diligently investigating the security risks and uncovering the vulnerabilities [8, 9, 10] within the CIoT. Some of these vulnerabilities arise due to misconfigurations or flawed protocol implementations. Beyond

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security risks, the issue of user privacy leakage in CIoT has garnered significant attention. Prior studies have examined user privacy preferences [11] and concerns [12, 13]. Moreover, recent findings indicate that victims of intimate partner violence (IPV) may encounter additional threats posed by concealed IoT devices [14].

To effectively deal with the above risks, network traffic analysis has been an essential tool for security and privacy research. By gaining insights into network traffic, one can understand user behaviors, identify network malfunctions, and unearth potential vulnerabilities; as a result, it is widely employed for network security protection such as real-time monitoring of malicious traffic within networks [15] or detecting malware [16, 17]. Meanwhile, using advanced data analysis and machine learning techniques, traffic analysis can construct website fingerprints [18, 19, 20], aiding in identifying phishing websites. Therefore, many researchers also conducted studies on the traffic of CIoT to analyze its security and privacy.

Existing literature predominantly focuses on general network traffic analysis, with a comparatively limited number of reviews specifically addressing CIoT traffic. Furthermore, these reviews often narrow their focus to individual issues, such as device identification or behavior classification. Given the escalating concerns surrounding CIoT device security and the widespread application of traffic analysis, there is a need for a comprehensive survey summarizing the current state of CIoT traffic security research.

In this paper, we systematically survey the five-year literature that analyzed CIoT traffic from the security and privacy perspectives. We aim to figure out the following research questions: RQ1: Are there any special new characteristics of CIoT traffic analysis different from general network traffic? **RQ2:** Looking at the traffic at present, what can we learn about CIoT systems from security and privacy perspectives? **RO3**: What new issues or challenges are yet to be solved by security researchers in the future regarding CIoT traffic analysis? Through a comprehensive survey of papers published in toptier conferences and journals (the literature retrieval method is presented in Section IV), we reviewed 310 papers in total relevant to CIoT traffic analysis and security or privacy. Based on these papers, first, we summarize the general framework of CIoT traffic analysis and discuss the new characteristics of CIoT traffic analysis different from general network traffic (**RQ1**). Second, we conclude the five application goals of the papers and further discuss the forefront of progress in each field (RQ2). At last, we summarize the challenges and shed new light on future research directions (RQ3).

Compared with surveys focusing on IoT security and

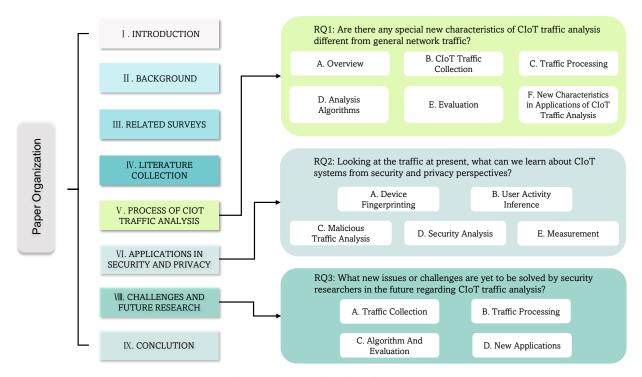


Fig. 1: The organization of paper.

privacy, traffic analysis, and IoT device fingerprinting, we systematically introduce the process of CIoT traffic and pay attention to its special characteristics. Moreover, we focus on what CIoT traffic can provide for the security and privacy community. The contributions of this paper are summarized as follows:

- As far as we know, this is the first survey focusing on CIoT traffic from security and privacy perspectives. We systematically reviewed 310 papers from January 2018 to December 2023, classified them according to application goals, and discussed their pros and cons in detail.
- We summarized the process of CIoT traffic analysis and discussed some special characteristics compared to general traffic analysis according to the analysis steps.
- We provide new insights on the challenges of analyzing CIoT traffic compared with general network traffic analysis and further figure out promising directions for future research.

Paper Organization. The organization of the paper is as follows: Section III introduces the basics of CIoT and traffic analysis. Section III summarizes the relevant surveys. We introduce the methodology for collecting literature in Section IV. For Section V, we present the CIoT traffic analysis process that we have distilled from extensive research and summarize the existing CIoT traffic datasets. We also extracted the unique characteristics of CIoT traffic and compared it with traffic analysis in other fields. Section VI discusses current works in detail according to their application goals. The challenges and future research will be discussed in Section VII. The organization of our survey is shown in Figure 1.

II. BACKGROUND

A. Consumer Internet of Things

CIoT, one of the most promising applications in the IoT field, refers to the application of IoT technology in consumer electronic products and devices. Smart homes and smart wearables are typical CIoT examples. Unlike other computing devices, CIoT devices typically have four *lifecycle phases* [21]: setup, interaction, idle, and deletion. First, the user setups the device, including configuring the network and account binding before using it. After setup, the user can use (interact) with the device. When there is no interaction, the device is in an idle state. Finally, a user may delete the device from the account when he/she needs to give up the usage rights of the device.

The representative CIoT scenarios are depicted in Figure 2. There are three main components: device, cloud, and user. Users can directly control devices locally or remotely through mobile Apps. Wi-Fi-enabled devices can communicate directly with remote users through cloud services. Devices using low-power protocols typically need to connect to a smart gateway, which then acts as an agent to the Internet. Furthermore, third-party platforms can be authorized to use device control APIs of the device cloud. Specifically, there are five primary device control methods:

- 1) Physical Control: Users can physically interact with devices. For example, the brightness of the light can be adjusted by touching the brightness bar on the smart light.
- 2) Multimodal Interaction: CIoT devices are equipped with various sensors and directly support multimodal interactions. Motion and temperature sensors enable devices to respond to environmental changes. For instance, motion sensors detect and report activities as someone passes by, which can then be utilized to control smart lights. Some CIoT devices support

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voice commands, for example, smart speakers like Amazon Alexa¹ and Xiaomi XiaoAi².

- 3) Local Area Network (LAN) Control: CIoT devices come with companion apps. When the device and smartphone are connected to the same local network, they can communicate via Bluetooth or Wi-Fi. The interaction includes basic device functions controlling, firmware updates, and general settings.
- 4) Wide Area Network (WAN) Control: When the smartphone and device are not on the same LAN, commands sent from the phone and status reported from the devices are first uploaded to the cloud, and then the cloud relays the messages.
- 5) Cloud API Control: In addition to companion apps, some platforms provide cloud API for third parties to access devices through OAuth authorization, which is the major way to enable automation control like IFTTT.

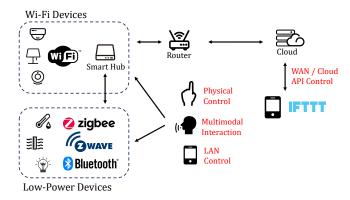


Fig. 2: The architecture of CIoT.

These various methods of controlling CIoT devices differ from those used by PC or mobile apps, presenting new challenges in traffic analysis and CIoT traffic analysis application goals.

B. Traffic Analysis

Traffic analysis has evolved significantly over the years and is a crucial aspect of network security, privacy, and quality of service management. Its primary aim is to extract valuable insights from network data [22]. The general network traffic analysis process can be divided into four steps: traffic collection, traffic representation, algorithm analysis, and evaluation.

According to different application goals, the captured traffic is usually divided into different analysis units. The granularity from fine to coarse is TCP connection, flow, session, service, and host. Researchers employ various analysis units to extract different types of features. TCP connection refers to a segment of traffic identified by certain TCP flags (such as SYN, FIN, RST) or TCP state transitions that indicate its initiation and termination. Flow is defined as a group of all packets sharing the same five tuples, i.e., source IP, destination IP, source port, destination port, and application protocol. Session, also known as bidirectional flow, encompasses both directions of traffic with the exchange of source and destination IP

addresses. Nevertheless, traffic characteristics applicable to a session sometimes do not directly apply to the corresponding two flows that form this session, especially when there is asymmetric internet routing. *Service* is defined as all traffic generated by a specific IP port pair. The *host* traffic refers to collecting all packets generated by a specific host, such as a switch or a lamp.

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Subsequently, features can be extracted from the analysis unit. In the early days, packet-level features dominated the landscape. This involves capturing, decoding, and analyzing individual packets to understand the nature of network traffic [23]. By inspecting the value in the packet header, researchers can extract rich information. Further, Deep Packet Inspection (DPI) delves deeper by examining the packet payload. However, the exponential growth of traffic and increased packet encryption necessitated the development of flow-level features. Flow analysis shifts the focus from individual packets to the communication between source and destination. It treats a sequence of packets from a source to a destination with the same protocol and port numbers as a flow [24]. NetFlow [25] and sFlow [26] are prominent tools facilitating flow-level analysis. Moreover, statistical analysis techniques have found their way into traffic analysis [27]. Statistical measures like mean and median are combined with packetlevel or flow-level features to generate statistical features. With the recent advances in Deep Learning (DL), raw packets can be transformed into images or sequences and fed into DL algorithms, thereby eliminating the need for manual feature extraction.

Next, we delve into the diverse algorithms employed in traffic analysis. These algorithms can be broadly categorized into machine learning (ML) and non-machine learning (non-ML) approaches. ML algorithms can be further divided into three categories: Traditional Machine Learning (TML), DL, and Reinforcement Learning (RL).

TML is a common branch of artificial intelligence (AI) that includes algorithms and models that learn patterns and make predictions or decisions based on data [28, 29]. Some commonly used TML algorithms include Decision Trees (DT), Support Vector Machines (SVM) [30], Random Forests (RF) [31]. Feature selection in TML algorithms is a crucial vet challenging step, often requiring significant time and effort. In contrast, DL models excel at automatically learning hierarchical features from data through various abstraction layers [32]. DL architectures like Convolutional Neural Networks (CNNs) [33], Artificial Neural Networks (ANNs) [34], Recurrent Neural Networks (RNNs) [35], and Graph Neural Networks (GNNs) [36] find wide applications across various fields, including traffic analysis. Meanwhile, the Transformer [37] architecture, primarily used in Natural Language Processing (NLP) research, also shows promise in certain traffic analysis tasks [38]. RL emerges as a unique subset of ML designed to equip agents with the ability to learn optimal behavioral strategies through trial and error [39]. Agents observe the environment's current state and select specific actions, continuously adjusting their behavior based on the received rewards or punishments [39]. This iterative process leads to the development of an optimal decision-

¹https://www.alexa.com

²https://xiaoai.mi.com

making strategy. Deep Reinforcement Learning (DRL) takes this concept further by combining DL techniques with RL algorithms [40], which empowers agents to learn complex behaviors and make decisions in high-dimensional environments.

Although AI-related algorithms have many advantages, sometimes these models can not provide the reasons for false positives or false negatives, and these algorithms are limited by data size [41]. To address these challenges, researchers have explored non-ML algorithms as alternative approaches. These include model-based method [41, 42], Locality Sensitive Hashing (LSH) [43, 44], and other techniques.

At last, studies will evaluate the performance of the algorithms using some metrics. In Section V, we will summarize the CIoT traffic analysis process and explain this framework in detail, considering the unique characteristics of CIoT devices.

III. RELATED SURVEYS

In this section, we will systematically introduce related surveys and emphasize their distinctions.

A. IoT Privacy and Security

With the widespread application of IoT devices, user privacy protection has become one of the core topics. Some researchers investigated works related to IoT privacy protection. Seliem et al. [45] reviewed existing research and solutions to privacy issues. Gupta and Ghanavati [46] conducted a systematic literature review on IoT privacy practices and technologies, providing a comprehensive summary of several issues related to privacy protection. Zavalyshyn et al. [47] focus on privacy-enhancing technologies for the smart gateway, as gateways are at the center of the entire system. In contrast, our research starts from the traffic perspective, concerning user privacy and exploring IoT traffic analysis related to security.

Several surveys focus on IoT security. Alrawi et al. [48] summarized the literature on IoT device security and organized a systematic evaluation method for assessing device security attributes. Abosata et al. [49] discussed the security risks brought about by implementing industrial IoT in smart cities and intelligent manufacturing, classifying attacks and potential security solutions, and thoroughly comparing different security mechanisms. Due to Home Automation (HA) systems being vulnerable, Wang et al. [50] studied the security of HA from the perspectives of attacks and defense and summarized relevant literature. Our work also includes issues in IoT security, such as malicious traffic detection. However, our attention lies in applying traffic analysis in IoT scenarios.

B. Traffic Analysis

With the widespread deployment of encryption, ML techniques have been widely applied in traffic analysis to overcome challenges in analyzing encrypted traffic that cannot be handled by packet header analysis or DPI. Papadogiannaki and Ioannidis [51] investigated the techniques, applications, and countermeasures related to encrypted network traffic analysis. They summarized relevant literature from four aspects: network analysis, network security, user privacy, and middleware

network functionality. Shen et al. [52] focus on applying ML techniques in encrypted traffic analysis. This work introduces four basic steps in network traffic analysis and organizes existing literature from four directions: network asset identification, network characterization, privacy leakage detection, and attack detection. Shahraki et al. [53] emphasize the advantages of online ML in traffic analysis. Compared to offline processing methods, newly arrived data can be processed promptly and effectively. Mathews et al. [54] investigated website fingerprint recognition defense methods. Bhatiaa et al. [55] specifically discussed the encrypted traffic of smartphones. These works focus on general network traffic generated by PCs and mobile phones rather than IoT.

C. IoT Fingerprinting

Meanwhile, network traffic analysis technology is gradually being extended to IoT device traffic analysis. These surveys are most relevant to ours. Sánchez et al. [56] reviewed device behavior fingerprints, covering not only smart home devices but also non-IoT devices such as PCs and personal smartphones. Jmila et al. [57] summarized the application of ML in the field of device classification, including data acquisition, feature extraction, classifier selection, and traffic classification granularity. They also highlight key issues to consider in device classification, such as feature costs and learning quality. Tahaei et al. [58] investigated the application of network traffic classification in different fields of IoT, including common IoT devices, smart cities, and healthcare systems. Differently, we focus on the traffic of CIoT devices, consisting of more application goals from the security and privacy perspectives.

In conclusion, although previous surveys explored IoT security and privacy and general traffic analysis, they do not provide a good answer to our three research questions about IoT traffic analysis proposed in the Introduction. Some surveys about IoT traffic analysis focus on specific relatively narrow application goals, especially device fingerprinting Jmila et al. [57] that partially overlaps with Section VI-A, but lack a holistic view of IoT traffic. Therefore, we consider our paper to be the first comprehensive review of traffic analysis in terms of CIoT security and privacy aspects.

IV. LITERATURE COLLECTION

To improve the quality of literature retrieval, we refer to some well-known public lists of academic conferences and journals in the field of network security. These include: the recommendations of Professor Guofei Gu from Texas A&M University [59], Professor Jianying Zhou from Singapore University of Technology and Design [60], Tsinghua University's Computer Science Discipline Group (TH-CPL) and the China Computer Federation (CCF) [61, 62]. We particularly emphasize conferences and journals in the A and B categories related to network and information security, computer networks, high-performance computing, and systems software and software engineering. Based on these sources, we categorize the journals and conferences into classes A and B by comprehensively evaluating their rankings across the above lists.

Rounds	Keywords
Initial	IoT traffic, security, privacy
First Round	IoT traffic, security, privacy, detection, fingerprint, vulnerable, attack, malicious, botnet, measurement
Second Round	IoT traffic, security, privacy, detection, fingerprint, identification, classification, vulnerable, attack, hack, malicious, anomalous, botnet, DDoS, measurement, smart home, intrusion

TABLE I: The keywords used in literature search.

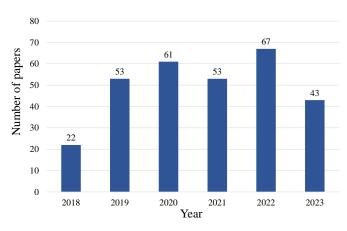


Fig. 3: The number of papers published from 2018 to 2023.

We adopted the snowball generations approach to expand the search keywords dynamically, ensuring both accuracy and breadth in our literature search. Initially, we manually retrieved CIoT traffic security-related papers from top-tier security conferences such as USENIX, S&P, NDSS, and CCS to identify search keywords. We conducted searches using the identified keywords "IoT traffic", "security", and "privacy" in all 17 Aclass conferences and journals, resulting in 3,006 papers over the past decade (2013-2023). "IoT Traffic" is a core keyword that must appear in the retrieved articles. "security" and "privacy" are auxiliary keywords, meaning at least one or more of them are included in the search results. By manually reviewing the abstracts and introductions of each paper, we carefully selected a subset of 75 closely relevant papers as the core literature for our survey. Based on the keywords and abstracts of these core papers, we expanded the auxiliary keywords to include these words: "security, privacy, detection, fingerprint, vulnerable, secure, attack, malicious, botnet, measurement". One or more of these keywords must be present in the abstract or keywords. Subsequently, we searched B-class literature from 2018 to 2023 using the expanded keywords. Employing the same method, we manually identified relevant literature and iteratively expanded the keywords in the collecting process (including their metamorphic tenses). Ultimately, the search keywords we used are listed in Table I, and the distribution of keywords across all papers is depicted in Figure 4. In total, we identified 310 relevant papers. The change in the number of articles over time is shown in Figure 3. We built an online website³ to hold the collected papers.



Fig. 4: The word cloud of keywords.

V. PROCESS OF CIOT TRAFFIC ANALYSIS

A. Overview

In this section, we summarized the process of CIoT traffic analysis and its new characteristics to answer RQ1 (Are there any special new characteristics of CIoT traffic analysis different from general network traffic?). The basic process included traffic collection, traffic processing, analysis, and application, which is depicted in Figure 5. The analysis process begins with traffic collection (Section V-B), which is quite different from network traffic analysis in other fields. The collected traffic forms the dataset for further processing. Existing public datasets are discussed in Section V-B3. Next, the section delves into traffic processing (Section V-C), highlighting feature classification and traffic representation. Following this, we introduce the typical algorithms used in CIoT traffic analysis (Section V-D) and common evaluation methods (Section V-E). At last, this section discusses the new characteristics and challenges of CIoT traffic analysis in applications compared to network traffic analysis (Section V-F).

B. CIoT Traffic Collection

1) Collection Process: The traffic collection process is the first step of CIoT traffic analysis and is the most different from general network traffic analysis. Firstly, CIoT devices come in a wider variety, and the traffic patterns of different types of devices may vary significantly. Secondly, CIoT devices exhibit diverse interaction patterns, necessitating consideration of traffic collection setups for different interaction scenarios. For example, to capture real user interactions, setting up a

³https://github.com/Rasin-Song/CIoT-traffic-survey

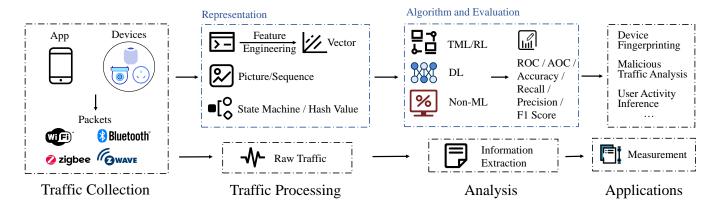


Fig. 5: The process of IoT traffic analysis.

smart home environment and involving a substantial amount of real-world physical testing is necessary. Thirdly, devices with different communication techniques (like Wi-Fi and Bluetooth) correspondingly require different link-layer traffic collection methods, posing challenges in constructing CIoT traffic datasets.

Figure 6 illustrates five methods to acquire traffic. Method (1)(2): Collection from the router. In this way, researchers can collect traffic at the inside or outside interface of Network Address Translation (NAT). The inside interface of the NAT router is connected to the private network, and the outside interface is connected to the public network. When capturing the inside interface, local IP addresses can be used to distinguish the traffic of each device. When capturing at the interface after NAT, traffic of all devices in LAN is mixed up. This is also the traffic gathering point by regular ISPs. OpenWRT [63] and hostapd [64] are popular tools for environment configuration. Method (3): Collection through receivers. Gathering traffic data from CIoT devices necessitates the utilization of specialized receivers due to their employment of diverse communication protocols besides Wi-Fi, such as Zigbee and Bluetooth. These protocols demand specific receivers to capture their respective signals. At this point, the captured packets are presented as link-layers. Method (4): Generation through the simulator. Due to the difficulties in collecting the malicious traffic of CIoT devices in the wild, researchers sometimes use simulators to generate the special traffic. Koroniotis et al. [65] utilize a tool, Node-RED, to simulate IoT devices in a virtual network. Method (5): Crowdsourced collection. "Crowdsourcing" refers to the practice of gathering information or data about network traffic through a large number of individuals, typically users or volunteers. In most cases, acquiring devices from various brands and categories can be costly, and simulating realistic user interaction traffic is challenging. So some researchers leverage crowdsourcing to gather data [66, 67].

2) Factors that Influence CIoT Traffic Collection: To sum up, considering the characteristics of CIoT traffic collection, we conclude several aspects that influence the dataset, including device number and type, collection method (self-collected in lab, crowdsourcing, or simulation), communication tech-

niques of devices, device control/interaction methods, device lifecycle phase, etc. Some features that make CIoT traffic analysis different from the general network traffic analysis are further discussed as follows.

Device Types. Quite different from PCs, CIoT devices have various types and vendors, e.g., smart lamps by Xiaomi, smart lights by Philips, refrigerators by Samsung, etc. Different devices have different functions and thus generate traffic with different characteristics. For example, smart cameras primarily transmit video, producing mass video traffic. But sensors like smart thermostats transmit fewer packets, consisting of real-time data or control commands. Smart speakers, on the other hand, include voice commands and responses, necessitating high-quality and low-latency transmission. Therefore, traffic of various device types presents different features and may pose specific challenges.

Collection Method. As illustrated above, collecting at the receiver can capture the link-layer packets. A special receiver is necessary for link-layer traffic analysis for devices that use communication techniques like Zigbee and Bluetooth.

Device Interaction. Referring to the device behaviors described in section II-A, device interactions primarily encompass the following methods: physical control, interaction through mobile apps, command via voice or other sensors, and cross-cloud APIs. Therefore, different interactions may involve different features in traffic. Also, some types of interactions are not easy to generate automatically, especially physical controls and sensor triggers.

CIoT Lifecycle Phase. Considering the traffic devices generate at different stages of their lifecycle is important. CIoT devices typically have several lifecycle stages, including setup, idle, interaction, and removal [21, 68]. In different lifecycle stages, the traffic of CIoT devices behaves very differently. For example, in the idle state, devices may have only heartbeat packets exchanged with servers, but the setup process may involve communicating with many parties (e.g., mobile app, DNS servers, multiple could endpoints).

3) Available Datasets: We provide an introduction to current datasets that are collected from the literature, as summarized in Table II. Among all self-collected datasets, the Mon dataset is the most frequently cited and contains the

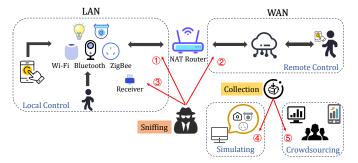


Fig. 6: Traffic collection setups

highest number of devices, followed by UNSW, YT, Ours, and PingPong.

NCSU IoT Lab Datasets (Ours) [69]. This dataset originates from the NCSU IoT Lab and comprises 8 CIoT devices and 3 non-IoT devices. Researchers simulated a smart living room environment, generating traffic through device interactions such as using voice assistants to control lights. These interactions were repeated 3-4 times per day.

YourThings Scorecard (YT) [48]. The YT dataset includes a large number of devices. It comes from the University of North Carolina and comprises 45 CIoT devices. The data collection spanned 13 days and encompassed interactions of devices. The one-day traffic is stored as a single PCAP file.

IoT Lab Traces Dataset (IoTDNS) [70]. The IoTDNS dataset originates from the same laboratory as the YT dataset. Unlike YT, the IoTDNS dataset contains DNS traffic data from 53 devices within a span of two months, specifically from August to September 2019. The DNS traffic for each month is stored as a single pcap file.

UNSW IoT Traces (UNSW) [71]. This dataset is from the University of New South Wales in Australia and comprises a total of 28 CIoT devices. Their capturing period spans over 6 months, but the authors only open 20-day data available publicly. The dataset contains traffic generated during user interactions.

BoT-IoT [65]. Koroniotis et al. designed a testbed to simulate various IoT sensors and botnet scenarios. They used four different Kali virtual machines to simulate various attacks, such as port scanning, DDoS, etc. Meanwhile, they use Ostinato to generate a lot of normal traffic.

Mon(IoT)r Lab Dataset (Mon) [21]. According to our investigation, the Mon dataset is currently one of the most comprehensive and finely categorized datasets available, encompassing 46 devices in the UK and 35 in the US. Researchers focused on the traffic related to device interactions and idle state. The interactions are further divided into four categories and labeled: traffic within the first 2 minutes of device powering, local app control, remote app control, and physical interaction. Authors created scripts to automate some interaction processes.

PingPong Dataset [72]. Similar to the Mon dataset, PingPong is also a dataset based on device behavior. It includes a total of 22 devices, with 3 of them being non-IoT devices.

However, unlike Mon's automated interactions, they collected data packets and categorized them into different events based on researchers' experience and knowledge.

HomeSnitch Datasets (HS and HS2) [73]. This dataset comprises traffic from 57 devices, including 26 devices that use low-power protocols. The collection spanned 8 days. 30% of traffic is triggered by apps, and 70% is generated by manual physical interactions.

IoT_Sentinel [74]. This dataset focuses on the traffic during the device setup phase based on which authors designed the device identification scheme. It contains packets generated by the 2-minute setup phase of 31 devices.

IoT-23 [75]. This dataset is derived from the Czech Technical University and includes both benign and malicious traffic. It encompasses only three devices: a speaker, a light bulb, and a doorbell. The malicious traffic is generated by executing malicious software on IoT devices. A total of 20 malicious scenarios and 3 benign scenarios were constructed.

N-BaIoT [76]. N-BaIoT plays an important role in the development of security research of CIoT devices and networks. It contains a comprehensive collection of network traffic generated by various IoT devices, including cameras, environmental sensors, and smart home appliances. This dataset provides labeled network traffic data, making it suitable for ML training.

IoT Inspector [77]. IoT Inspector is the largest known labeled dataset of CIoT traffic. By releasing an open-source application, the researchers crowdsourced the traffic from home networks. Since 2019, the dataset has included 7,000 users and network traffic from 65,000 devices. Authors have been collecting data since opening-sourced their tool online⁴. Obtaining the dataset requires contacting the authors.

NSL-KDD [78]. NSL-KDD dataset is a widely recognized dataset for network-based NIDS research. This dataset includes a wide range of simulated attacks, which can be categorized into four main groups: DoS, R2L, U2R, and Probing.

By inspecting the related dataset papers and Table II, we conclude shortcomings of current CIoT datasets. We observe that researchers have created more than 10 CIoT datasets, most of which are self-collected in the lab, possibly because of the convenience of labeling the traffic. Most devices of the datasets are from America and Europe, and the CIoT traffic in Asia is missing. We also note that the numbers and types of CIoT devices are very limited (only four of them consist of more than 50 devices), and the collection time of most datasets is earlier than 2021, which cannot reflect the tendency of CIoT devices today. Regarding communication techniques of CIoT devices, although most existing datasets include lowenergy communication protocols, they capture the packets at the router, ignoring the link-layer traffic analysis. Last but not least, current datasets do not label the lifecycle of devices in fine-grained. Therefore, in conclusion, there is a need for a more state-of-the-art comprehensive dataset, considering the characteristics and rapid development of CIoT.

⁴https://inspector.engineering.nyu.edu/

Name	Area ¹	Source ²	Categories ³	Nu	mber	Con	nmunication ⁴	Period	Size	e Time		Lifecycle ⁵		5
Name	Alea	Source	Categories	IoT	N-IoT	Wi-Fi	Low-energy	· Teriou	Size	Time	SU	ID	IR	DE
Ours	US	SC	10	8	3	✓	×	2020.3	11.5GB	11 days	×	✓	✓	×
YourThings	US	SC	15	45	0	\checkmark	\checkmark	2018.3	233GB	13 days	×	×	\checkmark	×
IoTDNS	US	SC	28	53	12	\checkmark	\checkmark	2019.8	366MB	2 months	×	×	\checkmark	×
UNSW	AUS	SC	17	28	3	\checkmark	\checkmark	2016.10	9.72GB	6 months	×	\checkmark	\checkmark	×
BoT-IoT	AUS	SL	5	5	0	-	-	2018.4	69.3GB	2 months	×	\checkmark	\checkmark	×
Mon(IoT)r	US&UK	SC	15	81	0	\checkmark	\checkmark	2018.9	12.9GB	-	×	\checkmark	\checkmark	×
PingPong	US	SC	12	19	3	\checkmark	\checkmark	2019	40.3GB	51 days	×	×	\checkmark	×
HomeSnitch	US	SC	13	57	0	\checkmark	\checkmark	2021.3	595MB	8 days	×	×	\checkmark	×
IoT_Sentinel	FI	SC	6	31	0	\checkmark	\checkmark	2016	61.4MB	-	\checkmark	×	×	×
IoT23	CZ	SC	3	3	0	\checkmark	×	2018	21GB	1 year	×	×	\checkmark	×
N-BaIoT	IL	SC	3	9	0	-	-	2018.3	240GB	-	×	×	\checkmark	×
IoT Inspector	-	CR	-	65000+	-	-	-	2019.4	-	-	-	-	-	-
NSL-KDD	US	SL	-	-	-	-	-	1998.5	4.06MB	7 weeks	×	✓	✓	×

TABLE II: The summary of existing datasets

- 1 "US" is the United States, "UK" is the United Kingdom, "AUS" is Australia, "FI" is Finland, "CZ" is Czech Republic, "IL" is Israel.
 2 In the "Source" columns, "SC" stands for self-collection, "CR" is crowdsourcing, "SL" is devices simulation.
- 3 These datasets consist of a total of 58 types of devices, including IoT devices (smart speakers, smart sockets, TVs, doorbells, door locks, various sensors, etc.) and non-IoT devices (mobile phones, routers, laptops, and game consoles, etc.).
- 4 In the "Communication" columns, "Wi-Fi" means the devices using WiFi protocol, "Low-energy" refers to the devices using the low-energy protocol like Bluetooth, ZigBee, and Z-Wave.
- "Lifecycle" column presents what device lifecycle phases are covered during the traffic collection. "SU" is setup, "ID" means idle, "IR" means interaction, "DE" is deletion.

C. Traffic Processing

After gathering original traffic, the second step is processing the data and extracting features or information for specific application purposes (e.g., device identification and abnormal detection).

1) Features Extraction: In this part, we introduce classic features extracted from network traffic.

Packet-level Feature. Packet-level features primarily involve fields from packet headers, such as IP address, port, TTL value, payload length, TCP initial window size, etc. Features from the TLS protocol header, such as encryption suites used during key exchange and plaintext information within ClientHello or ServerHello messages, are also usable.

Flow-level Feature. Flow features involve the overall information of a flow, such as the total input and output bytes of a flow, the transmission byte rate, flow duration, and more. In 2005, Moore et al. [79] summarized 249 flow features. Du et al. [80] used flow features to identify IoT devices, including flow rate variance, flow duration mode, time intervals mode between flows, etc.

Application-layer Feature. This feature includes field values in application-layer protocols such as DNS domain names and HTTP Host fields. DNS protocol features are a typical example. The investigation by García et al. [81] reveals that plaintext DNS protocol remains predominant compared to encrypted DNS protocols like DoH, DoT, and DoQ. It has prompted some studies to utilize DNS features. Perdisci et al. [70] uniquely identified devices based on the frequency of different DNS domain names requested by devices. Similar research includes [82, 83].

Statistical Feature. Based on packet-level and flow-level features, statistical characteristics of the traffic can be computed using statistical knowledge, which includes maximum, minimum, mean, variance, standard deviation, median, etc.

Deep Learning Feature. With the emergence of NNs, DL has been proven to surpass traditional machine learning methods in most areas. DL algorithms can automatically encode raw packets into sequences or images. For instance, Dong et al. [84] developed a traffic analysis framework based on sequence learning. They used a binary sequence to represent the protocols to suit the input requirements of the Long Short-Term Memory (LSTM) model.

It is worth noting that several tools facilitate extracting network features from raw pcap files, such as CICFlowmeter, Zeek, and Joy. CICFlowmeter [85], an open-source Java tool, can extract over 80 dimensions of features. For each flow, the CICFlowmeter generates a unique identifier called the Flow ID, composed of source address, destination address, and protocol number. Zeek [86], a network traffic analysis tool, is noted for security monitoring and allows custom feature extraction through its own Domain Specific Language (DSL); Its ZeekFlowMeter extension [87] supports IPv6 and boasts a similar feature count. Joy [88] differs by focusing on the application layer, outputting data in JSON, and specifically targeting TLS handshake details, DNS, and HTTP headers, thus complementing the feature set of the other tools.

2) Traffic Representation: In this part, we briefly introduce the representation of traffic. For ML, traffic is represented as a vector containing various features. For DL frameworks, different neural networks (NNs) require different traffic representations. For example, traffic can be viewed as time series data input into RNNs, where each time step represents device

activity within a certain period of time. For GNNs, the input can be a subgraph of network traffic, such as a communication graph (including connection relationships and communication patterns). Similarly, the set of packets can also be processed into images, suitable for models such as CNNs. For non-ML algorithms, the traffic is usually represented as hash value [43] or state transition graph [41].

D. Analysis Algorithms

This section summarizes the algorithms for analyzing CIoT traffic, which are summarized from papers reviewed in this survey.

- 1) Machine Learning Algorithms: ML algorithms analyze the input data to identify relationships and dependencies within the datasets [89]. These algorithms have gained development and refinement over the years and are popular in CIoT traffic analysis. ML algorithms can be classified into three types: Traditional ML, DL, and RL. Notably, as a supplement, Federated Learning (FL) is used in scenarios where multiple computational nodes are used for model training to ensure users' privacy by training the model locally at each node, sharing only model updates rather than raw data. We introduce ML algorithms in detail as follows.
- **a.** Traditional Machine Learning (TML). TML algorithms offer several advantages, including robustness and interpretability [90], making them valuable tools. Several TML algorithms are used for CIoT traffic classification, as introduced as follows.

DT [91] is a widely used classification and regression TML algorithm that represents the decision-making process using a tree structure, where each node corresponds to a feature or attribute, and each leaf node represents a category or value. SVM [30] is a commonly employed supervised TML algorithm primarily used for classification and regression problems. It constructs an optimal hyperplane to separate and predict data effectively. RF [31] is a TML algorithm used for classification and regression tasks. It utilizes multiple decision trees to make predictions, offering several advantages such as robustness, the ability to combat overfitting, and interpretability. Particularly, RF is widely employed in device fingerprinting. k-Nearest Neighbor (k-NN) [92] is a TML algorithm that does not rely on assumptions about data distribution but rather stores training data to make predictions for new instances based on their proximity to existing data points. k-NN identifies k nearest neighbors with a distance metric and then determines the predicted output by considering the majority class for classification tasks or averaging their values for regression tasks.

b. Deep Learning (DL). DL models mostly utilize multi-layer Neural Networks, which consist of interconnected neurons organized in layers to extract features. Each neuron receives input data, performs a weighted sum of the inputs, applies an activation function, and forwards the output to the next layer. By stacking multiple layers of neurons, DL algorithms can directly learn complex feature representations from raw data. Therefore, it excels in processing large input data and extracting valuable features from traffic. Representative

Deep Neural Network (DNN) architectures commonly include CNNs, ANNs, GNNs, and RNNs [33, 34, 35, 36].

CNNs constitute a specialized type of DL algorithm explicitly crafted for the analysis of visual data [33]. Comprising multiple layers, including convolutional, pooling, and fully connected layers [33], CNNs utilize backpropagation during the training process to update filter weights and optimize network performance. GNNs represent a category of NNs tailored to handle graph-structured data [36]. In graphs, nodes are connected by edges. GNNs use both the attributes of nodes and the graph topology to improve modeling. During a GNN's forward pass, each node gathers information from its neighbors, combines it with its own features, and updates its representation. ANNs consist of interconnected nodes or neurons that perform mathematical operations on input data to generate output predictions [34]. Autoencoder (AE) is a specific type of ANN, which consists of an encoder and decoder that work together to compress and decompress input data. RNNs are specifically designed to model sequential data [93]. The basic building block of an RNN takes an input vector and combines it with the previous state to produce an output and update the state. This output can then be used for prediction or can be fed back into the network as input for the next step. Notably, LSTM Networks are variants of RNNs that address the vanishing gradient problem and allow for the modeling of long-term dependencies in sequential data [94]. In traffic analysis, LSTMs can capture temporal dependencies and patterns in traffic over time.

- c. Reinforcement Learning (RL). RL [39] represents a form of ML that empowers an agent to learn and carry out tasks by interacting with its environment. This entails a trial-anderror process, wherein the agent receives feedback through rewards or penalties based on its actions. The primary goal of RL is to refine the agent's behavior, enabling it to maximize its cumulative reward over time. However, traditional RL is not widely deployed for CIoT traffic analysis for timewasting to find optimal solutions while exploring large stateaction space and suffering from the problem of explorationexploitation tradeoff [95]. To solve these problems, Deep Reinforcement Learning (DRL) [40] algorithms utilize advanced techniques such as artificial NNs to handle high-dimensional and continuous state and action spaces. For example, Deep Q-Networks (DQNs) [96] utilize DNN as function approximators to estimate value or policy functions.
- 2) Non-Machine Learning Algorithms: Although ML algorithms have the advantage of being adaptive, ML models may overfit the training data when the data is too small. When the environment changes, the model needs to be retrained [44]. Therefore, some researchers choose non-ML algorithms, which have higher computational efficiency. In the past, basic rule-based methods [97] and signature-based methods [98] played an important role. However, non-ML analysis methods develop as time goes by. In this subsection, we introduce two advanced non-ML algorithms as examples:

Locality-sensitive hashing (LSH) is a technique for quickly finding similar items in a large dataset. It first maps each item to a hash value and then uses a family of hash functions to

TABLE III: Evaluation metrics

Metrics	Detail
Accuracy	$(P_t + N_t)/(P_t + N_t + P_f + N_f)$
Precision & Recall	Precision= $P_t/(P_t + P_f)$ Recall= $P_t/(P_t + N_f)$
F1 score	2* Precision * Recall / (Precision + Recall)
ROC&AUC	ROC curve visually plots the true positive rate against the false positive rate at various classification thresholds. AUC represents the overall performance of the model by calculating the area under the ROC curve

 P_t : True positive example; P_f : False positive example; N_t : True negative example; N_f : False negative example.

group together items with similar hash values. This clustering facilitates the swift pinpointing of items that are probable to exhibit similarity. Such an approach is particularly pertinent in scenarios involving the identification of CIoT devices, as demonstrated by the work of Charyyev and Gunes [43] and Charyyev and Gunes [44]. Meanwhile, the traffic can be modeled as a state machine for analysis, which has proved its efficiency in NIDS. Duan et al. [41] construct CIoT packet-level automaton to profile traffic patterns, and Zhang et al. [99].

E. Evaluation

Algorithm evaluation refers to the process of assessing the performance and effectiveness of an algorithm in solving a particular problem or task. Various criteria, such as accuracy and robustness, can be considered when evaluating an algorithm. These criteria can be measured using different metrics, depending on the nature of the problem and the requirements of the application. When evaluating CIoT traffic analysis algorithms, several commonly used metrics are used to measure their performance, as introduced in Table III.

F. New Characteristics in Applications of CIoT Traffic Analysis

The traffic analysis process of CIoT and other fields (e.g., website traffic of PC) shares moderate similarities. However, due to the unique characteristics of CIoT traffic, some differences exist from general network traffic. Merely transplanting network traffic models into CIoT contexts is far from sufficient. The unique features of CIoT have led to numerous attempts to customize and improve the analysis process at every step to achieve specific application goals." In this subsection, we summarized the unique challenges faced by CIoT traffic analysis and its unique characteristics compared to network traffic (shown in Table IV).

1) Traffic Collection: The CIoT traffic data collection is more complex than PC or mobile apps, summarized in the following aspects. First, there are many types of CIoT devices, ranging from simple sensors to smart home systems, and each type of device differs in hardware and software design. Collecting CIoT traffic brings additional setup and financial burden compared to the PC or mobile phone traffic. In contrast to the limited type of operating systems, the quantity and variety of CIoT devices are expanding rapidly, making collecting

TABLE IV: Comparison of CIoT traffic and general network traffic

Items	CIoT Traffic	Non-IoT Taffic
Device Type	diverse	narrow
Protocol	diverse and customized	relatively diverse and standard
Interaction Mode	complex	easy
Communication Technology	various	mostly IP-based
Traffic Volume	small	large
Update Frequency	low	high
Available Datasets	relatively few	numerous

substantial training data for research purposes a significant challenge [100]. Second, CIoT devices usually have diverse interaction modes, including physical touch, environmental monitoring, cross-cloud trigger action, etc. These complex interaction ways make traffic collection difficult to automate fully. Third, besides Wi-Fi, CIoT devices also use various communication technologies, such as BLE, ZigBee, Z-Wave, LoRa, and NB-IoT. Each of these technologies has its own characteristics, as ZigBee focuses on creating low-power local mesh networks, while LoRa excels at long-distance, lowpower communication. Traffic analysis needs to consider the features of these different technologies and use the appropriate receivers to capture the packets in different layers. Finally, the operation of devices follows lifecycle phases and different phases present different traffic patterns. For example, the initial setup phase of the device may include many TLS key negotiations and domain name requests, while in the idle state, the device only sends heartbeat packets to maintain connections. Each phase needs different user setups that cannot be easily automatic either. Therefore, the complexity of collecting CIoT traffic prompts some researchers to tend to use public datasets instead of building their own ones. The number and size of datasets in the CIoT domain are less than other domains.

2) Traffic Processing: For traffic processing, the low power requirement and a wider range of communication protocols, device types, and lifecycle phases of CIoT bring new traffic characteristics for feature extraction. Firstly, CIoT devices typically have simpler hardware configurations than traditional network computing devices. This often results in smaller TCP buffer sizes [101] and directly affects packet transmission and network congestion control mechanisms. Meanwhile, the user-agent value field in HTTP, which is a common metric used in network traffic classification, may not always be effective because CIoT devices tend to use fewer online Web services. Additionally, our survey has revealed that the set of DNS domains contacted by CIoT devices is a popular feature used by researchers [70, 71, 83]. This is because CIoT devices communicate with a limited number of endpoints, resulting in limited and specific DNS requests. Therefore, the unique DNS queries or the remote IP addresses can serve as important features for CIoT traffic. Most notably, many manufacturers of CIoT devices design their own application layer proprietary protocols and implement encryption on this

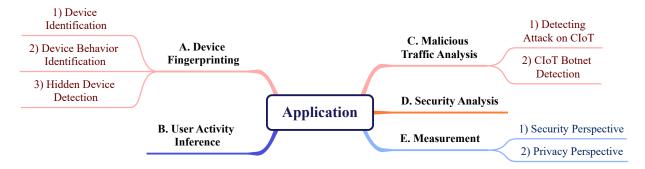


Fig. 7: The application purposes of CIoT traffic analysis in security and privacy

foundation. Considering the large number of CIoT vendors, commonly used traffic features may not behave well. These findings suggest that to identify and classify CIoT traffic more effectively, it is crucial to capture these unique characteristics keenly.

Secondly, as mentioned previously, CIoT devices deploy different communication protocols in the link layer (e.g., Wi-Fi and Zigbee), which can also help understand the behaviors of CIoT devices. Processing different link-layer frames may also require different features.

Lastly, traffic generated by CIoT devices varies significantly depending on their types and lifecycle phases. For instance, devices like plugs and lamps typically exchange only a few packets for interaction, while cameras require a much larger traffic volume to transmit video and audio data. Also, a camera's traffic generation patterns change depending on its state. In the idle state, it generates only a small amount of data, but it transmits a significant amount of data in the interaction state. This poses a challenge for statistical feature extraction. In contrast, traffic analysis in other fields, like website fingerprinting, does not involve the complexity of CIoT devices. The traffic of visiting websites generates many packets during short-term visits. That is, the volume of CIoT traffic is caused by a specific event or device type. Therefore, in some situations, it is necessary to pay more attention to packet-level features rather than solely focus on flow-level or statistical features commonly used in general network traffic.

3) Algorithm: The deployment features of CIoT bring some differences in general traffic analysis algorithms. First, due to frequent updates, network traffic characteristics change rapidly, presenting a significant challenge for models that depend on features. This necessitates frequent retraining of the model to adapt to updates. However, this dynamic is less common in CIoT devices due to their longer firmware update cycles [102]. As a result, once IoT traffic classification models are trained, they often retain their effectiveness for an extended period of time. Second, DDoS from compromised CIoT devices may be difficult to defend. The location of CIoT devices is dispersed, their number is large, and their bandwidth is limited; thus, the low bandwidth DDoS attack from CIoT botnet may pose additional difficulty for detection algorithms. Third, CIoT's dispersed location and low power requirement expect distributed ML. In practical scenarios, network traffic classification models can be deployed directly on

personal computers or servers. Both of these platforms possess sufficient computational power to support ML and even DL models. However, researchers tend to opt for deployment on gateways or servers in CIoT scenarios. Therefore, there is a gradual demand for distributed design like FL in CIoT traffic analysis.

VI. THE APPLICATIONS IN SECURITY AND PRIVACY

In this section, we answer RQ2 (Looking at the traffic at present, what can we learn about CIoT systems from security and privacy perspectives?). The existing literature can be categorized in five major directions based on application scenarios/goals of CIoT traffic analysis (as shown in Figure 7): Device Fingerprinting, User Activity Inference, Malicious Traffic Analysis, Security Analysis, and Measurement. The trends in the number of documents for different application purposes are shown in Figure 8.

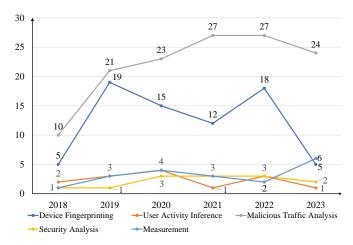


Fig. 8: Publication trends of different application purposes.

A. Device Fingerprinting

Device fingerprinting is one of the primary application scenarios of CIoT traffic analysis. Different types, vendors, and behaviors of CIoT devices generate traffic with unique characteristics. These characteristics can be used to uniquely identify devices and their behaviors, just like a fingerprint. The general process for constructing device fingerprints is shown in

Figure 9. By obtaining fingerprints from raw packets, attackers can predict device models and behaviors and further identify hidden devices, as illustrated below.

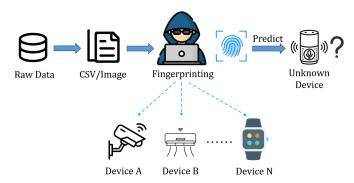


Fig. 9: The basic process of device fingerprinting

1) Device Identification: Device identification is the process of using unique traffic patterns to identify devices, e.g., their vendors, and device types/categories. Model identification can be used to perform fingerprinting attacks: attackers may use the information to discover vulnerable targets. On the other hand, it also can help regulators recognize these vulnerable devices. We summarized relevant papers in Table V. Earlier than 2017, the literature [74, 103, 104] focused on the preliminary application of traditional network traffic classification methods for CIoT. They aimed to achieve basic device recognition tasks and get higher accuracy. Later, in 2018 and 2019, improvements were made based on existing classifiers [105, 106, 107]. Moving into the year 2020, researchers [70, 108, 109] not only continued to optimize algorithms but also introduced more representative features that were better suited for CIoT scenarios. Considering the computing cost brought by a large number of features, works published in 2021 to 2022 [80, 110, 111] focus on feature reduction algorithms to acquire key features that enhance classification accuracy and efficiency. Moreover, they also considered greater device diversity and larger datasets [69, 111, 112].

Based on the process of traffic analysis (Section V), we summarize the contributions made by researchers to device identification. Note that one paper may contribute to multiple steps of the process and be discussed multiple times.

a. Traffic Collection. As for the traffic collection step, some work in the device identification field enriches the dataset. Specifically, they consider the devices that use low-energy protocols, certain kinds of devices (smart TVs or smartwatches), and the number of devices in the dataset.

Low-energy protocols, such as Zigbee, Bluetooth, and Z-Wave, transmit fewer data packets than Wi-Fi, presenting device fingerprinting challenges. Certain research [111, 119, 125] endeavors to tackle these issues and integrate devices that use low-energy protocols into their studies. Babun et al. [119] asserted themselves as the pioneering work that investigates the Zigbee and Z-Wave device fingerprinting framework. They constructed a density distribution based on inter-arrival time (IAT) by capturing packets at the link layer, representing the probability of a specific device generating data packets at a specific time. Subsequently, this density distribution is

divided into 300 equal intervals. The geometric area of these 300 intervals serves as the device signature. They conducted tests on 39 popular Zigbee and Z-Wave devices, resulting in accuracy rates of 91.2% for Zigbee and 93.6% for Z-Wave, respectively. Considering the asymmetry of learning and testing by ISPs during device identification, Ma et al. [125] monitored inbound and outbound packets and extracted Spatial-Temporal features to identify these devices that share a common IP (behind a NAT) from the ISP's perspective. The protocols used by the devices include Bluetooth, Zigbee, or LoRa. Kostas et al. [111] used the entropy of the payload as the feature, which also allows them to identify devices with non-IP and low-power protocols.

Some researchers [123, 124] focused on edge IoT devices such as smart wearables and smart TVs. Considering the personal health information contained in wearable devices like watches and bracelets, Aksu et al. [123] focused on fingerprints of wearable devices using the Bluetooth protocol based on Bluetooth packet characteristics. The algorithm utilizes the inter-arrival time of packets as a feature and can automatically select the optimal solution from over 20 classifiers. Additionally, they developed a test Android App that can generate Bluetooth messages between smartphones and smartwatches. In light of the advertising tracking and data leakage issues associated with smart TVs, Varmarken et al. [124] have identified the applications being used on TVs. They extracted fingerprints based on domains, data packets, and TLS information from the traffic. The fingerprint extraction relies only on a few packets, making their method lightweight and applicable to encrypted traffic.

Ahmed et al. [69] unprecedentedly considered a remarkable number of 188 devices. The experiment integrated six public datasets along with a self-collected dataset (the "Ours" dataset). They innovatively considered five different fingerprinting granularities: device instances, in which two devices of the same model are treated as separate instances; devices have unique make and model; devices have the same manufacturer and type; devices have the same manufacturer; devices have the same device category. Employing RF as the classifier, its accuracy surpasses 97% in all five cases.

Moreover, Bremler-Barr et al. [101] expanded the dataset to non-IoT devices. They proposed an approach to distinguish IoT and non-IoT devices. This offers insights for extracting background traffic (i.e., traffic from non-IoT devices like smartphones and PCs) in CIoT traffic analysis. Specifically, they devised three distinct classifiers. The first employs logistic regression based on features such as TCP window size and the number of unique DNS queries. The second classifier utilizes DTs, using features that are associated with the DHCP. The final is a hybrid one that combines the two previous approaches during different time intervals. Nonetheless, a flaw in this method is its potential confusion when dealing with smart devices like Android TVs that share the same software architecture system as mobile phones.

b. Traffic Processing. With the increasing diversity of devices, it may be challenging to distinguish them solely based on basic features that can be acquired easily through existing

TABLE V: Summary of device model identification literature

		Co	ntributions				Algorithm	Dataset	s Source	Com	munication	Callastian
Name	Year	Algorithm	Feature	Dataset	Feature	Type ¹	Name	Public Datasets	Self- collection	Wi-Fi	Low-energy	Collection Location ²
[104]	2017	√			Flow	TML	GBM, RF, XGBoost	Duasets	√	√		①
[113]	2017		√		Packet	TML	DT, RF, SVM		✓	√		3
[74]	2017		√	√	Packet	TML	RF		√	√	√	①
[103]	2017		√		Statistics	TML	RF		√	√		①
[82]	2018		√		Packet	NML	-	√		√	√	4
[105]	2018	√			DL	DL	LSTM	√		√		①
[114]	2018		√		Statistics	TML	RF	√		√		①
[100]	2018	√			-	NML	Apriori	√	√			①
[106]	2019	√			DL	DL	LSTM	√		√		①
[107]	2019	√			Packet, Statistics	TML	RF, Extra-Trees, AdaBoost	√		√		①
[115]	2019	√			Statistics	TML	k-NN, RF, DT, SVM, Majority Voting	√	√	√	√	①
[116]	2019	√			Packet, Flow, Statistics	TML	k-means		√	√	√	2
[71]	2019	√		√	Packet, Flow	TML	RF, Naive Bayes	√		√	√	①
[117]	2019		√		Packet	TML	J48 DT, OneR, PART	√		√	√	①
[118]	2019		√		Flow, Statistics	TML	k-NN	√		√	√	①
[44]	2020	√			-	NML	LSH		√	√		①
[84]	2020	√	√		Application	DL	LSTM		√	√		①
[119]	2020			√	Packet	TML	Bayes Net		√		√	3
[109]	2020	√	√		Application	DL	Self-designed		√	√	√	①④
[101]	2020			√	Statistics	TML	DT, Logistic Regression	√	√	√	√	①
[120]	2020			√	Packet	NML	-	√	√	√	√	①④
[121]	2020	√			Packet, Flow	TML	RF	√	√	√		①
[122]	2020		√		Packet	NML	-		√	√		24
[70]	2020	√	√		Application	NML	TF-IDF		√	√		①④
[110]	2021		√		Packet, Flow, Statistics	TML	DT	√		√	√	2
[43]	2021	√			Flow	NML	LSH	√	√	√	√	①
[123]	2021			√	Packet	TML	RF		√		√	①
[124]	2022			√	Packet	ML	Agglomerative clustering		√	√		①
[80]	2022		√		Packet, Statistics	TML	RF, Extra-Trees	√		√	√	①
[69]	2022			√	Statistics	TML	RF	√	√	√	√	①
[125]	2022		√	√	Packet	DL	CNN	√	√	√	√	①④
[111]	2022		√	√	Packet	TML	DT	√		√	√	①
[126]	2022		√		Packet, Statistics	TML	RF	√		√	√	2

^{1 &}quot;TML" means traditional machine learning, "DL" means deep learning, "NML" means traditional analysis. 2 "① - ⑤" corresponds to the five methods to acquire traffic in section V-B.

feature extraction tools (see Section V-C). Meanwhile, as mentioned above, extracting many features can bring computing costs to the algorithm.

Part of the works [103, 118] adopted personalized feature processing methods. Sivanathan et al. [103] made the first systematic study on smart device identification. They collected three-week traffic from 20 CIoT devices and extracted 11 distinct features by observing device activity patterns. They divided the values of each feature into 5 ranges called cluster bins. The cluster bins of different features are composed to distinguish different devices. This method achieved a 95% accuracy. However, as the number of devices increases, only 11 features with 5 gradations become insufficient. Marchal et al. [118] adopted another novel method of feature processing. They divided network traffic into multiple time-series "flows", which are defined as a collection of packets using a given MAC address and protocol. They then computed 33 periodic features obtained from the Discrete Fourier Transform (DFT) of traffic and employed the k-NN algorithm for device classification.

Some researchers [70, 82, 122] believe that the backend infrastructure for device connections has unique information. Guo and Heidemann [82] utilized unique communication server domain names to label CIoT devices; it can detect devices behind Network Address Translation (NAT) from aggregated traffic. However, distinguishing devices of the same type from the same manufacturer remains challenging. Similarly, Saidi et al. [122] identified devices by analyzing the domains and the backend infrastructure IPs and ports they communicate with. Likewise, Perdisci et al. [70] found that DNS domain names and their corresponding frequencies show significant discrepancies across various devices. They leveraged this as a feature and eliminated basic domain names (such as NTP) to accurately identify devices. However, DNS depends on device services; for instance, a TV of one brand equipped with voice services from another can lead to confusion and thereby reduce accuracy.

In addition, researchers [74, 109, 125] believe that device lifecycle, protocol, and time information should also be considered. Miettinen et al. [74] firstly considered the setup traffic. They selected 23 features from the first 12 packets during the setup stage to identify the types of new devices and further restricted their communication capabilities based on security levels. Analysis in fewer packets makes their method more lightweight. Yu et al. [109] innovatively employed BC/MC (Broadcast/Multicast) packet features to identify devices. The features primarily fall into three categories: 1) Identifiers, which can uniquely represent device models, such as hostnames in DHCP or answer names in mDNS. 2) Main features from BC/MC packets, which involve protocol fields and their corresponding values, along with pseudo-natural language features like unstructured textual content in mDNS payloads. 3) Auxiliary features, requiring tracking potential URLs generated during the packet transmission, which belong to active probing and used for assessment purposes only. To enhance the distinctiveness of features, Ma et al. [125] devised an efficient and scalable system using spatial-temporal traffic fingerprinting. They integrated both the temporal sequence of packets and their spatial correlations across the network. This approach provides a more comprehensive and accurate depiction of traffic, thereby boosting the effectiveness and performance of identification.

In addition to the feature of the network layer and above, some works [84, 113] considered link or physical layer features. Dong et al. [84] incorporated frame length and epoch time in the physical layer as features. Maiti et al. [113] innovatively extracted features from the encrypted link layer. The devices they used were categorized into 10 classes, with features including but not limited to frame type, size, arrival time, and rate. Experimental findings revealed instances of confusion between non-IoT devices like PCs and cameras. This indicates that there still are great challenges in utilizing link layer frames as the optimal distinguishing features.

In order to save classification costs, some researchers have added feature reduction technologies. We found that Genetic Algorithms (GA) are the most common [111, 117]. In the work by Aksoy and Gunes [117], 30 chromosomes correspond to the number of feature subsets. Each chromosome comprises a string of 0/1 representing feature selection. The GA starts with 30 chromosomes, initially filled with 0/1, and then runs a fitness function to ascertain the robustness of these features, resulting in an optimal feature subset. Kostas et al. [111] first employed the feature-importance-based voting method to eliminate unnecessary features from the initial set. Then, specific session-based or non-generalizable features are manually removed. After redundancy elimination, GA is applied to select the most suitable feature subset from the remaining 52 features. In addition to genetic algorithms, Santos et al. [114] incorporated the CfsSubsetEval algorithm into the feature selection process. This algorithm selects subsets from the original feature set with a high correlation with the target variable but a low correlation between features to reduce computational complexity. Wanode et al. [126] compared three distinct feature reduction techniques: SVD. PCA, and MI. They then utilized a random forest algorithm to classify 16 CIoT devices. This study found that achieving higher accuracy is more feasible with a feature set size of 21, with MI outperforming SVD and PCA significantly. Another part of works designed their own feature reduction algorithm [80, 110]. Chakraborty et al. [110] emphasize the varying costs associated with different features during the extraction process. As a result, they devised a cross-entropybased algorithm to tackle this concern. Similarly, Du et al. [80] built upon NSGA-III, introduced concepts like symmetric uncertainty and correlation coefficient. They propose multiple objective functions that reduce feature dimensions and filter effective features.

c. Algorithm. In this part, we discuss the contributions made by researchers in designing device identification algorithms. Early studies tended to favor TML algorithms. Gradually, researchers began considering constructing more complex identification frameworks based on basic classification models (e.g., SVM, *k*-NN, RF) or even neural networks. Meanwhile, with the development of edge computing, researchers began to consider distributed models. Apart from these approaches,

a few studies employ non-ML methods that can effectively shorten the calculation time and are very suitable for scenarios with high real-time requirements.

Some early work will consider using TML algorithms [104, 115, 121]. In 2017, Meidan et al. [104] trained a multi-stage meta classifier. The first stage differentiates IoT from non-IoT devices, and the second stage identifies specific device categories. However, the granularity of this approach only reaches device types (such as TVs, printers, motion sensors, etc.) and does not focus on specific device models. Similarly, Pinheiro et al. [115] demonstrated that using only packet statistics features, the RF algorithm outperforms k-NN, DT, SVM, and Majority Voting, achieving an accuracy of 96% in device identification. Moreover, in distinguishing CIoT traffic from background traffic and device event recognition, the accuracy of random forest reaches an impressive 99%. It is also the predominant reason why most research [71, 74, 103, 114, 121] rely on the RF algorithm. To handle the frequent addition of new devices, Ammar et al. [121] constructed a binary classifier for each device. This approach eliminates the need to retrain the entire model whenever new devices are added. They extracted features from network flows and payload, which were then input into a random forest algorithm.

Gradually, some studies have begun to consider integrated classifiers [71, 107]. Msadek et al. [107] emphasized the reduction of training data and the elimination of manual tuning. This is achieved by introducing a novel sliding window technique that dynamically segments traffic. As the activity of relevant traffic varies, the window automatically expands; otherwise, it contracts to discard irrelevant packets. To achieve higher accuracy, Sivanathan et al. [71] collected flow features from 28 CIoT devices over a span of 6 months, covering both interaction and idle phases of the devices while also retaining data from setup phases like TLS key negotiation and domain requests. They constructed a multi-stage classifier. The first stage employed a Naive Bayes Multinomial classifier, taking the bag of remote port numbers, domain names, and cipher suites as input. This bag comprises values and their corresponding frequencies in a matrix format. Then, flow attributes such as class and confidence for the bag, flow volume, and flow rate, among others, were used as inputs for the second stage, which leveraged an RF classifier to determine categories and confidence scores. This architecture achieved an impressive device recognition accuracy of 99%.

Subsequently, there were studies using DL algorithms[105, 106, 109]. Bai et al. [105] proposed a framework for automatically deriving features and extracting invariant dependencies across devices. They also constructed an LSTM-CNN cascade model to classify 4 device categories (hubs, Electronics, Cameras, Switches & Triggers). However, due to the limited richness of the dataset, while the algorithm performed well in binary classification, its accuracy dropped to 74.8% in the fourclass problem. Ortiz et al. [106] employed autoencoders to automatically learn features from traffic and probabilistically model devices as distributions of traffic classes. Further, their research uses a hybrid one-class SVM to infer labels for unknown devices. Yu et al. [109] innovatively utilized the traffic from local communication protocol. They developed a novel

multi-view wide and deep learning (MvWDL) framework. The six views constructed in the experiments are derived from the devices' BC/MC protocols. If two devices are similar in one view, they may differ in others. Meanwhile, they devised a hybrid-fusion multi-view artificial NN to achieve view fusion.

Although the above approaches achieve high accuracy in their designated scenarios, deploying the aforementioned algorithms at one network node presents challenges in scalability. Thangavelu et al. [116] developed a Distributed Device Fingerprinting Technique (DEFT) to tackle the same challenge. The DEFT controller maintains classifiers while gateways perform classification. SDN technology facilitates their coordination for identifying new devices within the network. While robust and manageable, DEFT is not lightweight, necessitating the collaboration of multiple distinct gateways to maximize system efficacy.

The above ML methods consume massive computing resources in practical implementation. Therefore, a novel approach based on LSH was proposed by Charyyev and Gune [43, 44]. This approach eliminates the need for feature extraction and can operate across all device states. More importantly, it doesn't require frequent model updates. LSH maps high-dimensional data to a lower-dimensional space and identifies nearest neighbors in the lower-dimensional space. The algorithm employs LSH functions to compute hash values of traffic, which are stored in a database. New devices are identified by comparing the stored values in the database. Perdisci et al. [70] integrated knowledge from other domains to develop algorithms better suited for the CIoT context. They analogized the Term Frequency-Inverse Document Frequency (TF-IDF) algorithm from document retrieval to device identification. TF and IDF represent term frequency and inverse document frequency, respectively, and this statistical technique assesses the importance of a term within a specific document in a collection. When employing a set composed of DNS request frequencies as recognition features, devices, and the requested domain names are treated as documents and their entries. This creates device fingerprints as TF-IDF vectors. Finally, target device reorganization relies on cosine similarity between vectors.

In addition to passive traffic capture and analysis methods, researchers have also adopted active probing techniques. Given the high complexity of CIoT device firmware analysis, studies have shown that there is often a time lag between vulnerability detection and exploitation. To address this challenge, researchers such as Feng et al. [100] have proposed an innovative method for automatic discovery and annotation of IoT devices, known as ARE. The ARE method focuses on the application layer response information and establishes a mapping between IoT devices and their corresponding official description websites by extracting banner information (usually containing details like device type and model). This lays the groundwork for building a comprehensive IoT device fingerprint database. Compared to traditional network scanning tools like Nmap, ARE has shown superior capabilities in searching for IoT devices. Especially when new IoT devices are connected to the network, ARE is able to dynamically and quickly learn and update the fingerprint information of new

devices.

Summary: According to our survey, the research about device identification accounts for 30%. Most researchers have chosen to improve their algorithms and feature extraction, reaching a relatively high accuracy on their dataset. Moreover, recent papers have specifically studied feature reduction techniques, which have also made breakthroughs in efficiency. In practical application scenarios, they still face a significant issue: traffic characteristics may be confused between devices of the same type but different models [69]. However, only a small part of the literature focuses on devices using low-energy protocols such as Bluetooth and Zigbee. CIoT devices use far more protocols than these, including LoRa, NB IoT, and more. In the future, identifying devices supporting various protocols will be a challenge. At the same time, we observed that most of the assumptions of the work are based on the attacker being able to invade the home router. If traffic is obtained after NAT (from the perspective of ISPs), effectively classifying individual devices needs more attention.

2) Device Behavior Identification: Device behavior is the current working status of devices; for example, the air conditioner is working or off, which could reflect user behaviors. Different device behaviors could generate different traffic, so the device behaviors can be identified by traffic analysis – device behavior identification. The triggering of device behaviors involves direct manipulation, LAN control, voice control, remote control, and control through the IFTTT interface (for more details, refer to Section II-A). We summarized the papers about device behavior identification in Table VI.

Early works used statistical features to identify device behavior [115, 127, 128, 134, 135]. Apthorpe et al. [134, 135] were among the early explorers who investigated the impact of diverse user behaviors on traffic patterns. They observed that user interactions can trigger abrupt changes in traffic behavior. Subsequently, Pinheiro et al. [115] found that devices show different packet length patterns in response to external commands. They employed a random forest classifier to identify device events. However, their scope of tested event types remained limited and couldn't distinguish similar behaviors among devices of the same model, such as opening/closing a speaker. Therefore, OConnor et al. [127] embraced a broader spectrum of device behaviors. They employed 13 features at the transport layer to characterize triplets, comprising the manufacturer, model, and activity. Additionally, they leveraged SDN technology to extend the OpenWrt firmware, enabling users to manage device behaviors. Similarly, Charyyev and Gunes [128] also used statistical features. Their contribution lies in evaluating and comparing the performance of 10 ML algorithms in classifying 128 device events stemming from 39 distinct devices.

Compared to previous work, Trimananda et al. [72] innovatively used packet-level features for the first time. They employ packet-pair sets between devices and servers to discern distinct device behaviors. However, the limitation of this approach lies in its applicability exclusively to the TCP protocol. Nonetheless, this method inspired subsequent investigations, and more importantly, they opened their collected data

(PingPong dataset), which has emerged as one of the classic datasets. Some researchers draw inspiration from PingPong and address its limitations [130, 131]. Duan et al. [130] used features similar to PingPong and resolved the constraint of being limited to TCP. Devices employing the UDP protocol can successfully extract signatures. Another advantage is that their signatures encompass more encoded information, making the impact of lost packet pairs minimal, while this may lead to false negatives in PingPong. Wan et al. [131] introduced a novel time-sensitive subsequence matching technique that generates more comprehensive signatures.

In addition to research on the behaviors of Wi-Fi devices, there is a growing body of work on studying the behaviors of devices using low-energy protocols [108, 129, 132]. Acar et al. [108] proposed a "multi-stage privacy attack" that encompasses the recognition of Wi-Fi, BLE, and Zigbee devices. The traffic is represented as a triplet, including timestamp, direction, and packet length, from which statistical features are extracted. Gu et al. [129] built a vulnerability detection framework called IoTGaze. It constructed wireless context by extracting the packet-level features of the device and identifying dependencies between events. This context is then used to detect anomalies by comparing it with the expected context extracted from the application description and UI using NLP. Researchers installed 183 SmartApps on the SmartThing platform and captured the communication traffic between 5 different types of Zigbee devices and hubs through sniffers. After evaluation, the accuracy of anomaly detection was 98%. Shafqat et al. [132] leveraged the low-power characteristics of the Zigbee protocol that message lengths are matched during encryption. It allows inference of application layer (APL) commands from encrypted traffic. Moreover, they found Zigbee devices periodically report attributes like battery levels and temperature to prevent device timeouts. This is so that attackers can use frame format guidelines to acquire an overview of APL commands and then infer device events based on payload lengths and reporting patterns.

Summary: The fundamental idea behind device behavior identification is similar to that of device identification, as both leverage traffic patterns to create fingerprints. However, the key difference lies in the fact that device behaviors only trigger minimal packet variations, making them more finegrained. In such cases, packet-level features are evidently more suitable than flow-level features. Numerous researchers draw inspiration from the work by Trimananda et al. [72] and employ patterns concealed within request-reply packet pairs to achieve this goal. It is noteworthy that DL techniques are rarely employed in the context of device behavior identification, potentially related to the dimensions of the sample.

3) Hidden Device Detection: While CIoT devices bring convenience for users, unexpected deployment of the device poses a threat to personal privacy. There have even been instances in which guests have found hidden cameras in Airbnb rental [136]. Therefore, some researchers have begun investigating ways to detect hidden IoT devices in unfamiliar environments. Existing approaches relying on radio frequency receivers are not entirely dependable, as they are susceptible to

		Co	ontribution				Algorithm	Data	Source	Com	Collection	
Paper	Year	Algorithm	Feature	Dataset	Feature	Type ¹	Name	Public Datasets	Self- collection	Wi-Fi	Low-energy	Location ²
[101]	2019	√			Packet	TML	k-NN,RF, DT,SVM, Majority Voting	√	√	\checkmark	√	①
[127]	2019	√			Flow, Statistics	TML	RF	√	√	√	√	①④
[108]	2020	√	√		Packet, Statistics	TML	RF		√	√	√	123
[72]	2020	\checkmark	√		Packet	TML	DBSCAN	√	√	\checkmark	√	23
[128]	2020	\checkmark		√	Statistics	ML	-	√		\checkmark	\checkmark	①
[129]	2020	\checkmark			Packet	TML	RF		\checkmark		\checkmark	3
[130]	2021	√	√		Packet	NML	-	√		\checkmark	√	23
[131]	2022	√	√		Packet	NML	-	√	√	\checkmark	√	①
[132]	2022			√	Packet	NML	-	√	√		√	①③
[133]	2023		√	√	Flow	TML	RF		√	√		2

TABLE VI: Summary of device behavior fingerprinting literature

interference from other legitimate RF devices such as smartphones and PCs [137]. This situation offers an opportunity for device detection based on network traffic. Taking cameras as an example, video traffic varies with user activities, where alterations in the visual scene trigger differences between adjacent frames [138]. This fluctuation in traffic patterns can be used to effectively confirm the potential cameras that are operational. This part presents relevant research that utilizes passive traffic capture to detect potential devices in unfamiliar environments.

Due to concerns regarding unauthorized video recording, some works focus on hiding cameras. Cheng et al. [139] proposed DeWiCam, a mechanism that utilizes smartphones to detect nearby wireless cameras. DeWiCam automatically analyzes physical and MAC layer data within interested rooms. By exploiting compression and fragmentation techniques used by cameras during video and audio transmission, differences in data transmission during both transient and stable states were employed as features. However, this method heavily relies on common transmission modes, which may not be generic across different manufacturers and may change with camera firmware updates. Wu and Lagesse [140] has designed a solution for dynamically detecting the presence of uploading cameras. However, this detection relies on comparing the similarity between user videos and videos uploaded by hidden cameras. The difficulty of detection significantly increases if a camera does not engage in uploading behavior.

Apart from detecting cameras, some studies have extended the scope of detectable devices to focus on Wi-Fi-based wireless sensor devices within a room [141, 142]. Singh et al. [141] leveraged the concept of "human motion" from Wu and Lagesse [140], which involves activating trustworthy sensor values and observing whether there exist similar traffic patterns from other devices. Additionally, they combined manufacturer

information retrievable from packet headers to identify specific device models. Furthermore, they introduced an innovative sensor coverage technique to locate the detected sensors. Sharma et al. [142] addressed device diversity by extracting device-specific attributes using multiple time scales. They also improved upon previous spectrum sensing methods [143], utilizing learned approximate transmission patterns over time to acquire device data transmission timing and channels. Their device fingerprint module computed features through an XGBoost classifier. The channel-aware module identified subsets of active channels through cyclic channel hopping. Lastly, a rough device positioning was achieved through RSSI-VIO. However, since this work employed MAC addresses for device classification, attackers could evade detection by frequently randomizing MAC addresses or random variations in transmission power.

Summary: In this section, we reviewed several representative works about hidden device detection. Compared to regular device traffic analysis, the scope of detectable information is quite limited. These efforts predominantly concentrate on the physical and link layers, utilizing wireless packet capture through network interfaces for 802.11 packets. Existing methods are primarily based on wireless protocols, with very few addressing devices that use protocols such as Zigbee or Bluetooth. Moreover, existing methods have a high dependence on much prior knowledge and limited scalability, which requires a sufficient understanding of testing objects. Therefore, one of the future challenges will be how to expand the applicability of the model while reducing false positives.

B. User Activity Inference

The leakage of user privacy has remained a prominent topic in the realm of network traffic analysis. Many works have been conducted to detect user web browsing history [144],

^{1 &}quot;TML" means traditional machine learning, "DL" means deep learning, "NML" means traditional analysis.

^{2 &}quot; \bigcirc " corresponds to the five methods to acquire traffic in section V-B.

whether specific websites have been visited [20, 145], and user interactions in mobile Apps [146, 147]. Similarly, attackers can also infer users' personal information through the traffic of CIoT devices. In this subsection, we discuss the privacy concerns arising from CIoT traffic.

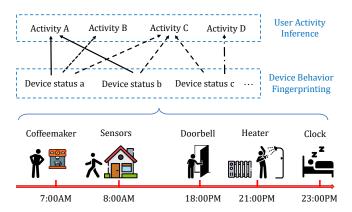


Fig. 10: The model of user activity inference

Firstly, it is possible to infer user activity from CIoT traffic. Once attackers obtain the residents' daily routines and activities, they can commit crimes. Therefore, some researchers established a mapping relationship between traffic patterns and user activities, which always use fingerprints of devices and their behaviors [108, 112, 138, 148]. The basic process for user activity inferring is shown in Figure 10.

Inspired by the work on inferring user activity through network traffic, Li et al. [138] discovered that differential coding in surveillance cameras could inadvertently leak sidechannel information. Distinct body movements by users can lead to significant inter-frame differences between packets. Consequently, they used frames and applied k-NN and DB-SCAN for activity recognition, categorizing them into known and unknown activities. In addition to cameras, Acar et al. [108] have considered scenarios with more device types. They modeled user activities through multiple stages. The first three stages identified the device type, whether it is active, and its specific state. Then, they modeled user activities using by Hidden Markov Model (HMM) in the final stage based on this information. However, this model only achieved a coarsegrained user behavior representation, identifying aspects such as whether a user remotely controlled a device or moved between locations, without providing a more nuanced insight into users' specific behaviors. Unlike the previous scenario, Gu et al. [148] innovatively focuses on 5 Zigbee devices on the SmartThings platform. They first constructed device behavior fingerprints. Subsequently, they inferred the user's ongoing activities. Finally, combined with the idea of dynamic programming, they revealed user activity dependency, which can be used to infer user's living habits, routines, and even installed IoT applications. However, they did not evaluate their methods on Wi-Fi devices where their communications are more complex. Based on the previous works, Wan et al. [112] considers the presence of missing or unordered device events and develops an approximate user activity signature matching algorithm. Additionally, they design a heuristic trimming step to address multiple matches involving overlapping CIoT device events.

Different from the above work, Subahi and Theodorakopoulos [149] studied the traffic behavior and privacy leakage problems on the App side, including the interactions between users and CIoT devices, encompassing interaction types and the exposure of sensitive Personally Identifiable Information (PII) and its type. They employ three random forest classifiers to achieve this goal. The first classifier distinguishes interaction event types between Apps and devices; the second gauges the presence of sensitive PII, non-sensitive PII, or no PII; and the third identifies the specific types of PII. By scrutinizing packet data, they unveil the correlation between different App communication domain names and specific interaction types. By combining execution sequences and packet lengths, they can further inspect whether the traffic contains sensitive user data. By training the model, they can indicate the presence of privacy-sensitive data in unknown traffic. However, it's important to note that this study doesn't provide a solution for companion Apps using fixed certificates.

Summary: The core challenge of inferring user privacy from CIoT traffic is identifying dependencies between device events and user activities. There is an opportunity for a more refined exploration of diverse events, particularly in multiuser scenarios, where different household members trigger devices at distinct time intervals, just like Wan et al. [112] did. Addressing multi-user scenarios presents a significant challenge for designing algorithms to distinguish the activities of different users.

C. Malicious Traffic Analysis

Like device fingerprinting, malicious traffic analysis is another popular direction in CIoT traffic research. In this subsection, we introduce the malicious traffic analysis papers from two perspectives: detecting attacks on IoT and CIoT botnet detection.

1) Detecting Attack on CIoT: Due to low hardware configuration and long update cycles, CIoT devices are vulnerable to various attacks, including Scanning attacks, Brute Force attacks, DoS attacks, and Cryptojacking [157]. Therefore, many researchers devoted themselves to detecting attack traffic targeting CIoT devices [99, 150, 151, 152, 153, 154, 155, 156], which is also called intrusion detection. We summarized these research in Table VII.

Most of these work provided the ability to detect several general attacks [151, 152, 154, 155], as is represented by DDoS and Scanning attacks. In 2019, Anthi et al. [151] presented a NIDS with 3 layers in order to detect 12 attacks (e.g., DDoS, MITM, Scanning) in a CIoT network environment. Firstly, the first layer classifies the normal behavior of each IoT device with the help of J48 DT. Then, they identify the malicious attack packet at the attack period in the second layer. At last, in the third layer, the malicious packet will be classified by attack type. In 2020, Charyyev and Gunes [155] proposed LSAD, which is based on LSH, in order to detect a variety of attacks, such as ARP Spoofing and DDoS attacks. Unlike ML-based algorithms, their method does not need to

		Co	ontribution			Algoi	rithm	Data S	ource	Com	munication	Collection
Literature	Year	Algorithm	Feature	Dataset	Feature	Type ¹	Name	Third-party Datasets	First-party Datasets	Wi-Fi	Low-energy	Location ²
[150]	2021	√		√	Statistics	TML+RL	RF, iForest, MAB-RL		\checkmark	√	√	3
[151]	2019		√	√	Flow, Packet	TML	DT		√	√	√	①
[152]	2020	√	√		Flow, Packet, Statistics	TML	RF, PCA		\checkmark	√	√	①
[153]	2021	√		√	Packet, Statistics	TML	iForest, DT		\checkmark		√	①
[154]	2022		√	√	Statistics	TML	SVM		\checkmark	√		2
[99]	2018	√		√	-	NML	DFA		\checkmark		√	①
[155]	2020	√			-	NML	LSH	√			√	①
[156]	2020	√	√		Flow, Packet, Physical	NML	-		\checkmark		√	3

TABLE VII: Summary of literature about attack on CIoT detection

extract features from data. LSAD provided more than 97% of accuracy in their evaluation, which is equal to or better than ML-based algorithms. Similarly, aiming at specific attacks, in 2022, Tekiner et al. [154] presented a lightweight traffic-feature-based method to detect CIoT Cryptojacking, which is claimed to be the first research to focus on IoT Cryptojacking. They trained with an SVM classifier and proved that their algorithm can obtain 99% accuracy with one hour's training data.

Furthermore, special attacks targeting IoT devices are also detected. In order to solve the IoT security sensor tampering issue, Pathak et al. [153] came up with two algorithms to detect sensor tampering attacks: an unsupervised learning algorithm using iForest and a supervised learning algorithm CART based on C4.5 DT. Through their evaluation, they found that the supervised learning algorithm CART behaved better than the unsupervised learning algorithm because it found abnormality both in abnormal and some normal situations.

Additionally, aiming at the attacks on low-energy CIoT devices, researchers also came up with solutions [99, 156]. CIoT SmartApp is a type of program running on the cloud

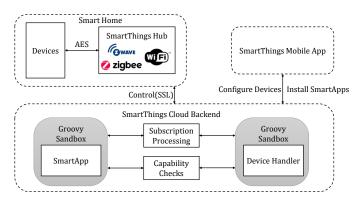


Fig. 11: Architecture of SmartThings platform [99].

(as shown in Figure 11), which is possible to be attacked

and raise threats to CIoT devices. Aiming at dealing with the over-privileged accesses and spoofing attacks in the application layer of CIoT SmartApp, in 2018, Zhang et al. [99] represented a typical study focusing on the identification of malicious SmartApps through traffic analysis. They initially extracted Deterministic Finite Automata (DFA) based on textual descriptions and user interfaces. Each individual App can be represented by a corresponding DFA. By monitoring encrypted traffic captured from wireless channels, they compare the observed state transitions associated with a behavior to the predefined DFA. If a match fails, it suggests the possibility of a malicious App. Notably, this research targeted Zigbee and Z-Wave devices on the SmartThings platform. However, the scalability of this approach when dealing with more complex functionalities and a greater number of states in Wi-Fi devices remains the problem for further consideration. To detect attacks on the commonly applied Bluetooth Low Energy (BLE) devices, in 2020, Wu et al. [156] put forward a nonintrusive monitoring system, BlueShield, aiming at detecting Spoofing attacks in BLE devices with the help of both cyber features and physical features(e.g., Advertising Interval, Received Signal Strength Indicator). The unique design of BlueShield makes it possible for it to be deployed on lowcost platforms without modification for BLE devices and its users. Through evaluation, they proved that their method could detect Spoofing attacks in BLE effectively and clearly.

When facing unknown attacks, researchers put forward algorithms based on unsupervised learning [150, 152] and RL [150] algorithms. In 2020, Wan et al. [152]introduced a security monitoring system IoTArgos, which detects attacks such as Scanning and Brute-force at the system, network, and application layers of Smart Home IoT system by a supervised learning algorithm RF, and integrated an unsupervised learning algorithm principal component analysis (PCA) to detect zero-day or unknown attacks. Through the evaluation, IoTArgos can detect anomalous activities that target Smart Home IoT devices with high precision & recall. In 2021, Heartfield et al. [150]

^{1 &}quot;TML" means traditional machine learning, "NML" means traditional analysis, "RL" means reinforcement learning.

^{2 &}quot; \bigcirc " corresponds to the five methods to acquire traffic in section V-B.

presented MAGPIE, the first Smart Home NIDS, which is able to autonomously adjust the function of its underlying anomaly classification models to a smart home's changing conditions (such as newly-added devices, new automation rules, and human interaction) to detect both known and unknown threat in Smart Home IoT network. Researchers applied a probabilistic cluster-based reward mechanism to RL and combined them with supervised learning classifier RF and unsupervised learning model iForest to classify traffic. Evaluation experiments in a real-home smart home environment containing Wi-Fi and Zigbee devices showed that MAGPIE provides high accuracy.

Summary: According to our survey, nowadays, researchers have designed specific algorithms to detect various attacks aimed at a variety of CIoT devices. The intrusion detection research is mostly based on non-ML and TML algorithms; meanwhile, in order to detect unknown threats, researchers combine unsupervised learning algorithms into their research. However, although DL-based detection methods have already been an important part of intrusion detection work of general network and IoT traffic, there is still unexplored research content in CIoT till now. It is possible that the need for storage may be a limit for DL-based detection methods to be applied in the intrusion detection of the CIoT network environment.

2) CIoT Botnet Detection: DDoS attacks, mostly raised by botnet networks, which are formed by compromised CIoT devices, such as Mirai, Satori, and BASHLITE, have been a huge threat and even brought serious loss to the network environment. One of them, the notorious Mirai, had caused massive network outages [183]. According to these situations, we point out that it is of great importance to research the detection of CIoT botnet. Until now, many researchers have been concentrating on the detection work of CIoT botnet (As shown in Table VIII). Based on the research method, we summarized them into four kinds as follows.

a. Traditional ML-based Detection Methods. Among our survey, at present, many researchers use DT and RF algorithms to detect CIoT botnet traffic in the research of CIoT botnet attack detection based on TML [175, 177, 180]. In 2020, OKUR and DENER [177] compared two different ML algorithms in detecting normal traffic and the attack traffic from botnet. In their evaluation, the supervised learning algorithm (J48 DT) behaved better than the unsupervised learning algorithm (Expectation Maximization).

Furthermore, some researchers [175, 180] concentrate on the feature selection of the CIoT botnet traffic. In 2019, Dwyer et al. [175] came up with an analysis method based on DNS in order to detect CIoT botnet. They put forward a DNS feature set and evaluation variety of TML classifiers, including RF, k-NN, and Naïve Bayes. RF classifier behaved the best among them (shows 99% accuracy) and indicated that the feature-set based on DNS can significantly reduce the time of botnet detection. Next year, Shafiq et al. [180] claimed that some ML model made mistakes in malicious traffic detection for their choice of feature. They designed an algorithm called CorrAUC based on the wrapper technique to filter features and combined the AUC metric to select features. The authors evaluated four ML algorithms(C4.5 DT, SVM, RF, and Naïve

Bayes) and pointed out that RF and C4.5 DT are the more effective algorithms.

In addition to the centralized approach, distributed DDoS detection has also been proposed by researchers. In 2021, Doshi et al. [179] proposed a novel NIDS based on a modified version of the Online Discrepancy Test (ODIT) to timely detect and mitigate Mongolian DDoS attacks characterized by widely distributed attack sources and small attack scales. The researchers used a k-NN-based algorithm to calculate the abnormal traffic conditions at each node. They then used a cooperative detector to aggregate the local statistical data of each node and obtain the global statistical data to determine whether an attack had occurred. Upon detecting a DDoS attack, the system employs a mitigation algorithm that identifies and blocks traffic from offending nodes. This approach was validated using the N-BaIoT dataset, IoT testbeds, and simulations, proving its effectiveness against various DDoS scenarios. Their research acknowledged the need for regular updates to the NIDS to accurately reflect network dynamics and features in practical applications.

Based on the detection of CIoT botnet, researchers have made deeper discussion in some campaigns of CIoT botnet [182]. In 2022, Torabi et al. [182] proposed a system to detect and analyze scanning campaigns of CIoT botnet. The author extracted the traffic from CIoT devices using the Shodan search engine and over 6TB network from the Dark web and detected compromised devices by examining whether they emitted unsolicited scanning. In their discussion, they pointed out that it is possible that their work is affected by the dataset, which was collected too early in August 2017. It is possible that some of these compromised devices had already been removed from the Internet. Meanwhile, the researchers also detected and classified the scanning campaigns in compromised CIoT devices based on DBSCAN. Then, they grouped CIoT devices with similar scanning behavior and showed the campaign feature of CIoT botnet.

b. DL-based Detection Methods. Till now, as one of the most popular types of ML algorithms, DL has plenty of applications in botnet detection [38, 160, 161, 162, 163, 164, 165, 166, 167, 168, 169, 170, 171, 172].

We analyzed from method and found that most researchers use NNs to detect CIoT botnet [160, 161, 162, 164, 165, 166, 167, 169, 170, 171, 172]. Various NNs are applied to detect CIoT botnet [165, 166, 170]. In 2019, Hwang et al. [165] proposed a DL-based IoT malicious traffic detection mechanism. Researchers extracted flow features with the help of CNN and classified traffic with AE. The authors evaluated the mechanism with the traffic dataset collected from their Mirai network and USTC-TFC 2016 dataset and pointed out that the mechanism can achieve nearly 100% accuracy. In 2021, Nakip and Gelenbe [170] designed an Auto-Associative-Dense-RNN-based detection method to detect Mirai botnet attacks. Researchers evaluated their method with the Mirai attack traffic extracted from the Kitsune dataset. By comparing with Linear-model-based Least Absolute Shrinkage and Selector Operator (LASSO) model and the model based on the TML algorithm k-NN, the author proved that their method is better

TABLE VIII: Summary of the CIoT Botnet Detection Literature

		Co	ontribution			A	lgorithm	Data S	Source	Com	munication	Collection
Literature	Year	Algorithm	Feature	Dataset	Feature	Type ¹	Name	Third-party Datasets	First-party Datasets	Wi-Fi	Low-energy	Location ²
[158]	2021	√			Packet	NML	-		√	√		①
[159]	2023	√			DL	DL+RL	CNN	√		√	√	4
[160]	2019	√	√		Flow, Packet, Statistics	DL+FL	RNN		√	√	√	25
[161]	2022	√	\checkmark		DL	DL+FL	DNN		√	√	√	①
[162]	2022	√			Statistics	DL+FL	AE	√		√	√	①
[163]	2022	√			DL	DL+FL	CNN	√		√		①
[164]	2023	√			DL	DL+FL	AE	√		√		①
[165]	2019	√			DL	DL	AE, CNN	√	√	√		①
[166]	2020	√	√		Flow, Statistics	DL	VAE, RNN	√		√	√	5
[167]	2020	√			DL	DL	AE	√		√	√	①②
[168]	2020	√			Statistics	DL	GAN, AE	√		√		①
[169]	2020		√		DL	DL	AE, LSTM	√		√	√	1
[170]	2021	✓	\checkmark		Statistics	DL	RNN	√		√	√	1
[171]	2022	√			DL	DL	AE	\checkmark		√	√	4
[38]	2022		\checkmark		DL	DL	Transfomer	√		√	√	1
[172]	2023		\checkmark		DL	DL	CNN	√		√	√	4
[173]	2022	√	√		Statistics	ML	ELM	√		√	√	2
[174]	2019	√			Flow, Packet, Statistics	TML	RF, Bagging, AdaBoost, Voting	√		√	√	4
[175]	2019	√	√	√	Packet, Statistics, Application	TML	RF		√	√	√	1
[176]	2020	√		√	Statistics	TML	FCM		√	√	√	①
[177]	2020	√	√		Statistics	TML	DT	√		√		①
[178]	2021	√			Statistics	TML+FL	k-NN	√		√	√	①
[179]	2021	√		√	Packet	TML	k-NN	√		√	√	①④
[180]	2021	√	√		Statistics	TML	DT, RF			√	√	1
[181]	2022	√			Flow	TML	Metric Learning	√		√	√	①
[182]	2022	√		√	Flow	TML	DBSCAN		√	√	√	5

^{1 &}quot;TML" means traditional machine learning, "DL" means deep learning, "RL" means reinforcement learning, "ML" means machine learning, "FL" means federated learning and "NML" means non-machine learning.

than k-NN and LASSO in accuracy, true positive rate (TPR) and true negative rate (TNR). Meanwhile, in order to solve the problem that only known botnets can be detected offline by existing technology, in 2020, Kim et al. [166] proposed a new botnet detection method based on the Recurrent Variational Autoencoder (RVAE). They construct a model by combining VAE and RNN. This model can detect unknown botnets and provide the ability of real-time, online detection. In their evaluation, they evaluated with CTU-13 dataset and showed that their algorithm is comparable to existing methods. By testing in a variety of scenarios (including botnets not used for training), they demonstrated the robustness of the method

in detecting unknown botnets.

Till now, based on our survey, most of the researchers who use DL to detect CIoT botnets focused on the detection effect of their methods without conducting comparative tests or only compared their methods with TML methods to show their advantages. Only a few researchers compared their methods with other DL methods in their evaluation; however, some of these methods did not train with datasets collected from CIoT devices.

In addition, the weak computing power and low storage of devices in the CIoT network challenge the deployment of DL models. To solve this problem, researchers tried to

^{2 &}quot;①-⑤" corresponds to the five methods to acquire traffic, see section V-B.

combine FL with DL [160, 162, 163]. In 2019, Nguyen et al. [160] presented a self-learning distributed system for detecting compromised devices in the CIoT network. This system uses GRU Algorithm (a novel approach to RNN that requires no human intervention and labeled data) and trains with the unlabeled crowdsourced data collected from the client network to detect real-time traffic anomalies online. Researchers collected three datasets: activity, deployment, and attack. They combined the activity dataset and the attack dataset to choose their parameter. Then, they evaluated their method with the deployment and attack datasets to simulate the deployment environment and achieve high TPR and 0.00% FPR. In addition, they proved that the application of FL did not bring an obvious negative impact on TPR and FPR. In 2022, Nishio et al. [162] trained an anomaly detection FL model based on AE to detect botnet traffic to detect easily infected software. When assessed using their datasets collected from CIoT devices and simulating malware traffic, their method demonstrated enhanced efficiency in detecting malware under reasonable conditions. They got a more efficient detection model than AE and iForest models, which were trained centralized, and AE models were trained with datasets stored in individual clients.

Based on the above algorithms, researchers conducted further research to solve the problems of privacy leakage and deployment difficulty. In 2022, Zhao et al. [163] pointed out that FL-based NIDS may cause privacy breaches because the transmitted model data may be used to recover private data. Meanwhile, not independent and identically distributed (non-IID) private data can affect FL in training effect, especially the distill-based FL. The typically large models are difficult to deploy. In order to solve these problems, they proposed a Semi-supervised FL NIDS scheme (SSFL), which is based on knowledge distillation of unlabeled data and used CNN as a classifier and discriminator network to build the model. They claimed that SSFL is the first FL method based on distillation in traffic classification. Researchers used the CNN discriminator to guarantee the distillation effect under private non-IID data. They evaluated SSFL with the N-BaIoT dataset and showed SSFL has the advantage in classifying performance and communication overhead compared with common algorithms such as FL-based algorithms and LSTM-based algorithms.

c. RL-based Detection Method. RL is a novel type of ML algorithm. At present, some researchers have proved that RL-based algorithms are effective in general traffic analysis [159]. Therefore, Baby et al. [159] designed a RL-based NIDS. The author adopts four DRL algorithms: Actor-Critic (A2C), Proximal Policy Optimization(PPO), Kronecker-Factor Approximation (KFA) and Deep Q-Learning Network (DQN) to detect malicious DoS and DDoS traffic raised by CIoT botnets and proposed two defending strategies against Label Flipping Attack (LFA), which is possible to trick ML systems: Label-based Semi-supervised Defence (LSD) and Clustering-based Semi-supervised Defence (CSD). In their evaluation, researchers tested DRL models in different attacking and defending situations with three datasets, NSL-KDD, IoT23,

and N-BaIoT, which are constructed mainly by botnets formed by compromised CIoT devices and pointed out that DRL algorithms are much more successful than TML and DL algorithms.

d. Non-ML-based Detection Methods. In recent years, MLbased botnet detection methods have become popular among researchers; however, non-ML-based methods are an important expansion of thinking of ML-based methods. In 2021, Reed et al. [158] proposed a lightweight detection framework aiming at detecting "Slow DoS" attacks in resource-constrained IoT networks. "Slow DoS" attacks are often raised by devices that can only provide low bandwidth and limited device resources. It is characteristic of its stealthy attack, which is difficult to detect. In their research, they used a set of only four attributes to analyze in two steps for a real-time IoT network, classified packets into 3 types: legitimate nodes (LN), genuine nodes with slow-to-intermittent connections (SN), and malicious nodes (MN), to real-time detect "Slow DoS" attacks in the form of Slowloris in an efficient and reliable way. This lightweight NIDS framework can classify genuine nodes experiencing slow or intermittent network connections and malicious nodes in an effective way; we illustrate their detection framework [158] in Figure 12.

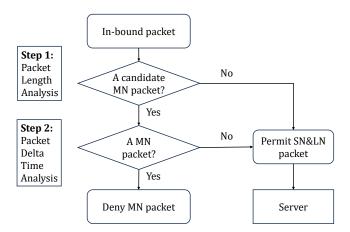


Fig. 12: Real-Time Slow DoS Detection Framework [158].

Summary: With the rapid popularization of CIoT devices, attacks raised by those compromised devices' botnets have seriously threatened network security. Till now, researchers have proposed various detection methods. Researchers mainly use DT and RF in the TML domain and use NNs in the DL domain. Meanwhile, distributed thinking is applied by researchers to solve the problem of the deployment of ML and DL models. However, in most researchers' evaluations, they usually concentrate on the effect of their algorithms or compare them with other types of ML algorithms but lack horizontal contrast. In addition, non-ML detection methods are a necessary supplement of ML-based methods.

D. Security Analysis

Recently, with the rapid growth of the amount of CIoT devices, security risks of CIoT networks have increased due to the lack of safety training of users and the design flaws

of devices or network structures, which are more likely to be attacked. In order to solve these problems, researchers started to work on security analysis of CIoT devices based on traffic. We show these papers as follows.

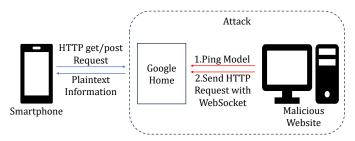


Fig. 13: An attack case of Smart Home IoT system [184].

Aiming at solving vulnerabilities in CIoT networks, such as vulnerability due to user wrong configuration, in 2018, Jia et al. [184] proposed a mechanism to detect vulnerabilities in the communication of Smart Home IoT devices. Their method took captured files as inputs and constructed a traffic graph with these captured messages. Meanwhile, they identified the correlated subgraphs with the help of checking every attributevalue pair that is associated with these messages. At last, they quantified their vulnerability by the sensitivity level of each keyword. The author tested their method on their Smart Home IoT system and identified 6 attack cases; we showed one of them as an example in Figure 13. With the evaluation test, they proved the effectiveness of the method. In order to solve the problem of credentials that are used insecurely, in 2022, Zhang et al. [185] proposed an analysis framework, KingFisher. They prevent communication from attacks such as privacy leakage or device hijacking by identifying shared credentials, tracking the using condition and checking nine security properties of credentials such as randomness and the ability to resist brute force attacks. The authors analyzed the credentials in actual IoT deployment scenarios with more than 3,500 devices and pointed out that all the scenarios suffered insecurely used credentials. In 2023, James et al. [42] designed a complex framework to cast an IoT system attack graph based on Finite State Automata (FSA) to detect vulnerabilities in the network. This framework identifies vulnerabilities that can cause the most damage in the network with the help of a shortest pathbased algorithm and determines the possibility of each arc of the attack graph with the help of a Common Vulnerability Scoring System (CVSS).

Summary: Recent advancements in the CIoT have led to increased security risks due to users' mistakes and inherent design defects in CIoT devices or network structures. However, different from safety analysis of the general network environment, CIoT security risks are not only raised by attackers [42] but by mistakes made by users or designers [185]. Therefore, with the popularity of CIoT devices, it is of urgent need to find threats in the CIoT network and devices and propose solutions.

E. Measurement

As an increasing number of smart devices enter the market, researchers did measurement studies on CIoT traffic in order to gain insights into CIoT's behavior, security, and privacy status. IoT backends, vendors, communication protocols (TLS), IoT botnet, traffic destination, and private data exposure are considered in the studies, summarized in Table IX.

1) Security Perspective: First, the general deployment and security status of CIoT devices is studied. Kumar et al. [186] collaborated with Avast Software, an antivirus company, and conducted extensive empirical analysis on traffic of 83 million devices across 16 million homes collected by user-initiated network scans in Dec. 2018. This study reveals widespread global adoption of CIoT, with significant regional variations in device types and manufacturers. Security vulnerabilities, including open services, weak default credentials, and susceptibility to known attacks, are also explored, highlighting geographical disparities even within specific brands.

Meanwhile, as TLS is a prominent security protocol used in CIoT, Paracha et al. [188] analyzed two years of TLS traffic and assessed the security of TLS connections established by IoT devices and how these connections changed over time. They revealed that TLS 1.2 was the most widely used version, while TLS 1.3 was less frequently adopted and often faced issues that the server may not support. Additionally, of the devices they tested, approximately 1/3 of devices were found to be vulnerable to interception attacks during TLS practices, potentially exposing sensitive data. Their contribution lies in providing relevant recommendations for standardizing TLS to indicate future directions. Similarly, Huang et al. [77] expanded the dataset through crowdsourcing. They developed a tool called "IoT Inspector" to collect the traffic of 44,956 smart devices worldwide. By analyzing the data, researchers found that many device vendors used outdated TLS versions and that third-party advertising and tracking services on TV were prevalent.

Saidi et al. [190] emphasized that the security and functionality of IoT devices often rely on the IoT backend, that is, the server on which the device downloads resources or the cloud-hosted for computing, etc. However, the public has limited knowledge about the location, strategies, and market share of these backends. By analyzing ISP's passive traffic data, they discovered that approximately one-third of the traffic was exchanged with backend servers spanning across regions. Additionally, some protocols used non-standard ports or reused web ports. Ultimately, this work constructed a detailed map of IoT backend servers, revealing the relationships among these backend providers.

Besides the security issues of CIoT devices, some researchers [187, 189, 191] focused on the compromised ones, especially the IoT botnet. Noroozian et al. [189] evaluated the impact of two ISP security policies on Mirai: closing propagation ports of malicious software and strengthening regulatory efforts. By analyzing four years of dark web data, the research revealed that the strategy of closing ports to reduce the attack surface had no significant effect. In contrast, improving overall network health and remediation efforts significantly reduced the infection rate of Mirai. This provides guidance for ISPs in formulating strategies to prevent the spread of Mirai. Almazarqi et al. [191] investigated the impact of AS structural properties on the spread of Mirai-like IoT

TABLE IX: Summary of measurement literature

Topic	Year	Measurement Description
	2019	Evaluating the deployment of CIoT devices in different regions and security issues that include open services and weak default credentials [186].
	2019	Investigating the Hajime botnet [187].
	2020	Measuring insecure TLS implementations and the phenomena of third-party advertising and tracking services [77].
Security	2021	Assessing the security of TLS connections established by IoT devices and how these connections changed over time [188].
	2021	Evaluating the impact of two ISP security policies on Mirai: closing propagation ports of malicious software and strengthening regulatory efforts [189].
	2022	Constructing a detailed map of IoT backend servers and revealing the relationships among these backend providers [190].
	2022	Investigating the impact of AS structural properties on the spread of Mirai-like IoT botnets [191].
	2019	The first group to study cross-regional data privacy on a large scale, which includes the destination of traffic, encryption status, distribution of plaintext and ciphertext content, as well as the possible exposure of device information [21].
	2020	The privacy risk about speaker misactivations [192].
Privacy	2020	A large-scale empirical measurement focusing on Home Security Cameras (HSCs) in China and identifying three major behaviors that may leak user privacy: traffic surge, traffic regularity, and traffic rate change [193].
	2021	Extracting the non-essential destinations of the device [194].
	2023	Focusing on how the smart speaker ecosystem, especially Amazon Echo, collects, uses, and shares data [195].
	2023	Measuring the privacy leakage of local network interactions of IoT devices [196].

botnets. They pointed out that commonly and widely used IP blacklist databases are incapable of tracking concentrated botnets. At the same time, they found that if the degree of an AS, that is, the number of direct connections between this AS and other ASes, is low, then the AS is more likely to become a host for malware downloaders. These works have opened up ideas for ISPs to formulate security strategies in the future. Herwig et al. [187] investigates the Hajime botnet, a distinct entity from the Mirai botnet, focusing on its distributed design and use of a public peer-to-peer system as a command and control infrastructure. Through detailed measurements, including active scanning and passive DNS backscatter traffic collection, the study reveals that there is a higher number of compromised IoT devices than previously reported, and new vulnerabilities can significantly increase the size and capabilities of IoT botnets. These devices use a variety of CPU architectures, and their popularity varies widely between countries.

Summary: CIoT traffic security measurement offers valuable insights and guidance for building a more secure CIoT ecosystem. Firstly, the user data used for measurements should be legally authorized and subject to thorough desensitization to ensure the privacy of user data. Secondly, current research (such as [187, 189, 191]) primarily focuses on a few malicious software families, such as the Mirai botnet. However, as IoT malware becomes more complex, future research may pay attention to various types of malicious software families.

2) Privacy Perspective: In addition to security measurements, researchers are also working to measure the leakage of private information by devices from the traffic perspective.

"Mon(IoT)r Research Group" from Northeastern University has done a series of work related to CIoT privacy measurement [21, 192, 194, 195, 196, 197, 198]. Ren et al. [21] is the first to study cross-regional data privacy on a large scale. By capturing traffic from 81 CIoT devices distributed across laboratories in the UK and the US, they delved into aspects like the destination of traffic, encryption status, distribution of plaintext and ciphertext content, as well as the possible

exposure of device information. Their findings revealed that almost half of the device traffic was directed towards thirdparty entities or support services. Furthermore, a notable observation was that over half of American devices and the majority of British devices engaged in cross-regional data transmission. Next year, Dubois et al. [192] focused on the privacy risk of speaker misactivations. By playing different TV shows on Netflix around seven speakers for 134 hours, they found that smart speakers have a 95% possibility of misactivations with unintentional and listed the wake words that caused misactivations for the specific speaker. Similarly, Iqbal et al. [195] focuses on how the smart speaker ecosystem, especially Amazon Echo, collects, uses, and shares data. They exposed that Alexa Echo smart speakers collect user data and share it with third parties. The data is used to target ads and track users' interests, which may raise concerns about user privacy. By blocking traffic to different destinations of the CIoT device, Mandalari et al. [194] extracts the non-essential destinations of the device. The study found that 52% of devices communicated with non-essential destinations. Among them, smart TVs and cameras contacted numerous non-essential destinations. Different from the above studies, Girish et al. [196] measured possible privacy leakage of local network interactions of CIoT devices. Through a systematic analysis of the protocols used by devices in LAN, the authors identified various threats, including uncontrolled dissemination of sensitive information and device vulnerabilities. The research also revealed that the companion apps and third-party SDKs could potentially abuse user-space discovery protocols to access local network information, resulting in privacy infringements.

Another group of researchers [193] did a large-scale empirical measurement focusing on Home Security Cameras (HSCs) in China. They identified three major behaviors that may leak user privacy: traffic surge, regularity, and rate change. A sudden increase in traffic indicates that video uploading is in progress; the regularity change in traffic can be used to infer whether users are active and specific activities; traffic rate change can reflect changes in user activities. Furthermore,

they found that premium users contribute the majority of the traffic (up to 95%), making them more susceptible to behavior inference attacks.

Summary: The results of privacy measurements indicate that users' private information may be exposed by CIoT. Various measurement studies have confirmed that devices frequently connect to third-party servers, which may lead to violations of local regulations such as the GDPR. Therefore, regulators and researchers need to focus on whether the declarations regarding third-party organizations in privacy policies are accurate and whether these declarations are properly enforced by devices. Furthermore, firmware updates on CIoT devices can alter existing behaviors, necessitating evaluations of the impact of time on measurement results. In addition, many studies focus on the devices in the EU and the US but neglect other regions, e.g., Asia.

VII. CHALLENGES AND FUTURE RESEARCH

In this section, we answer RQ3 (What new issues or challenges are yet to be solved by security researchers in the future regarding CIoT traffic analysis?) by summarizing future work. We conclude the challenges and future research directions of CIoT traffic analysis based on the analysis process and application goals.

A. Traffic Collection

Compared to PC and mobile apps, CIoT devices possess many special characteristics (many types, lifecycle, low-energy communication techniques, etc.), which influence the traffic collection process, as discussed in Section V-B. In the following part, we summarize the key issues brought by CIoT and potential future research directions regarding CIoT traffic collection.

1) More Comprehensive Datasets: As we discussed in Section V-B, CIoT traffic collection is the most challenging compared with general network analysis like website or application fingerprinting. Building a dataset containing the traffic of thousands of mobile Apps or websites is relatively easy, but setting up a physical CIoT environment/testbed is more timeconsuming and costly, especially considering numerous CIoT vendors, types, and models. As outlined in Section V-B3, the currently accessible CIoT datasets remain relatively limited in comparison to network traffic. Although researchers around the world proposed several datasets independently and even Huang et al. [77] collected traffic of thousands of devices by crowdsourcing, an up-to-date, unified, and large-scale CIoT traffic dataset available for researchers is still important. Considering characteristics in CIoT, the dataset should cover the complete CIoT lifecycle and be fine-grained labeled, thus enabling various application goals in the future. In the future, researchers may propose a CIoT traffic collection standard and collaboratively build a continuously updating and privacypreserving CIoT traffic dataset worldwide. Lastly, as shown in Table II, almost all datasets are self-collected in the lab (except IoT Inspector). Therefore, researchers need a realworld dataset that does not expose any users' privacy to test their methods in practice.

- 2) Cost-minimal CIoT Traffic Collection Methods: As discussed above, building a large CIoT traffic dataset is important but time-consuming and costly. This variability is due to the diversity of interaction modes among device types, such as physical control and automation rules, as discussed in Section II-A. Ren et al. [21] to some extent make the collection process automated by Monkey Application Exerciser included in Android Studio. However, not all these interaction modes can be fully simulated in an automated way and thus require much human effort. Therefore, automating the traffic collection process to save human costs is a worthy future direction. Meanwhile, traffic simulation generation can effectively reduce economic costs. This is a common and easy approach in general network traffic analysis, particularly for network assessment and constructing datasets of malicious traffic [199, 200]. However, the construction of datasets through virtual environments remains uncommon in the CIoT domain, possibly also in part due to various user interaction modes. Therefore, how to simulate vivid CIoT scenarios and generate realistic traffic has not been solved yet, as far as we know.
- 3) Non-IP Traffic: Most works focus on analyzing the TCP/IP network layer traffic and above. However, as discussed in Section V, CIoT devices deployed many non-IP communications such as Zigbee, Z-Wave, and Bluetooth. Most existing works [103, 115, 117, 118] connect these non-IP devices to a smart hub and collect traffic at the router, which only contains IP packets. In a different attack scenario where the attacker is near the victim's home, the attacker can also infer much information about the user and devices through link-layer packets; for example, Gu et al. [148] successfully inferred users' behaviors through Zigbee packets. Thus, we need a comprehensive CIoT traffic dataset that contains many communication protocols/techniques, including Zigbee, Z-wave, Bluetooth, 4G/5G, etc. This will enable future works to analyze and infer information in different scenarios.
- 4) Malicious CloT Traffic: Finally, the latest research shows that datasets containing malicious traffic have certain limitations in network traffic[201]. Similarly, the construction of CIoT malicious traffic datasets is also a topic worth exploring. When it comes to the datasets used to detect CIoT malicious traffic, we should also discuss them from two different angles. At first, it is absolutely necessary to construct a CIoT botnet attack traffic dataset for CIoT botnet detection research. However, most researchers have recently done their research with some popular third-party datasets such as BotIoT, N-BaIoT, and IoT23. It is time-consuming and challenging for researchers to construct a dataset that can be used in training due to the high volume of equipment and distributed attack sources in real CIoT deployment situations. Nevertheless, the research of CIoT botnet detection does have a need for the timeliness of dataset, especially since most algorithms are not designed to detect attack traffic raised by unknown botnets. Secondly, in our survey, almost all researchers collect and construct their datasets by building CIoT platforms, making simulation experiments, or designing honeypots by themselves to research the detection attack traffic on CIoT. It can be a limitation of the research development to detect attack traffic

on CIoT because data collecting is costly and time-consuming. For these reasons, it is important for future work to construct a dataset including attack traffic aiming at attacking devices in multiple protocol categories (including Wi-Fi, BLE, Zigbee, etc.) to avoid researchers' biases.

B. Traffic Processing

- 1) Local Traffic: In Section V, we analyze the differences in traffic between CIoT devices and traditional computing devices. Researchers may consider these distinct characteristics when designing and implementing traffic analysis. We observed that most research focuses on analyzing the communication traffic between devices and the cloud. However, comparatively, there is a scarcity of research on local communication traffic analysis between CIoT devices and companion apps, but local communication could also show much information (as Girish et al. [196] did). Therefore, how to effectively analyze local communications, including low-power communication protocols, is an interesting research topic.
- 2) Vendor Proprietary Protocols: Most works learn information about devices by standard protocols [70, 109, 122]. On the other hand, due to the requirements for security and real-time communication, many manufacturers prefer to use proprietary/private encryption protocols based on UDP. These protocols often render standardized monitoring tools ineffective, and thus, developing new techniques with protocol reverse engineering ability becomes a key task in analyzing these devices.
- 3) Feature Optimization: Cutting-edge research on network traffic has proposed many methods of traffic representation. For instance, Xie et al. [202] employed more robust TLS features. Bronzino et al. [203] presented a framework and system that evaluates the system-level costs of various traffic representation methods. This system can promptly transform traffic and generate diverse representations for algorithms. The work by Zola et al. [204] employed a graph-based approach that involves temporal dissection and data-level preprocessing. They addressed class imbalance issues and enhanced the supervised node behavior classification. Holland et al. [205] automated various aspects of traffic analysis and introduced the tool nPrint for generating unified packet representations.

Also, when evaluating the correlation between each feature and the target variable, methods such as correlation coefficients and mutual information can be used to measure the degree of association between features and the target. Meanwhile, a variety of feature selection optimization methods in ML could be employed, including tree-based feature importance evaluation algorithms, recursive feature elimination (RFE), LASSO, GA, etc.

C. Algorithm And Evaluation

1) Open-world Problem: Different from fingerprinting of OS or websites, the types/models of CIoT devices are countless. That is, the dataset for training the model cannot cover all CIoT devices worldwide. Thus, the model's ability to identify devices in an open world needs to be effectively verified.

To some extent, traffic generated by companion mobile apps may also reflect the behavior of devices and could be used to improve the accuracy of device fingerprinting.

- 2) New Types of Device: Edge CIoT devices and multifunctional devices have not received the attention it deserves. Smart TVs, as typical edge CIoT devices, mostly feature Android-based operating systems, which could cause their traffic characteristics to be confused with the background traffic of devices such as smartphones. This overlap may obscure the intrinsic features of smart TVs. Moreover, as smart TVs add functions like voice assistants, their traffic becomes more like that of smart speakers, deepening the confusion. Therefore, analyzing the traffic of multifunction devices, like smart TVs with voice assistance and sweeping robots that combine cameras, brings new challenges to existing algorithms focusing on single-function devices.
- 3) Unified Standard Evaluation: Our survey shows a lack of comparative evaluation work in a unified standard test set (dataset and algorithm), as is described in VI-C. The scattered CIoT ecosystem, unfortunately, leads to immethodical evaluations. We advise creating a unified standard evaluation test of the algorithms that solve the same target, which will greatly benefit future research.
- 4) Applying New AI Techniques: Since 2023, the success of large language model (LLM) [206], especially ChatGPT, has appealed lots of researchers applying it to address problems in various computer science fields. When it comes to the CIoT traffic analysis domain, it is possible to try LLM on different application targets of the CIoT traffic analysis domain in the open world. Online Machine Learning [207] could also find its place [160, 166]. As discussed in Section VI, at present, most of the existing algorithms require a complete dataset containing many samples for training. It is important to detect newly-raised attacks on time by a model trained by incomplete CIoT traffic, as there is always newly manufactured equipment.

D. New Applications

CIoT comes with complex architecture and rich application scenarios. Different from fingerprinting mobile apps or websites, CIoT is a system that involves multiple components working collaboratively including clouds, apps, etc. Besides the application goals introduced in Section VI, traffic analysis could possibly provide more insights into the CIoT ecosystem. First, leveraging companion apps to understand CIoT devices is becoming usual nowadays. Security testing and research on the device encounter limitations due to firmware not being public [208]. Therefore, some studies opt to inspect the companion apps by static analysis to unveil potential risks of user data exposure [209, 210], and some take apps as the fuzzing proxy [211]. We believe that the traffic of CIoT companion apps is a valuable research area for understanding the CIoT ecosystem, e.g., the supply chain ecosystem, which remains to be thoroughly studied. Second, the rich application scenarios of CIoT suffer various new attacks [48, 50]. As introduced in Section VI-C, many researchers use traffic to detect malicious behaviors, such as [152], [150], and [99]. With new attacks being discovered continuously, in the future,

researchers may propose new robust and lightweight methods based on traffic to tackle these upcoming and existing attacks. Thirdly, existing works prove that CIoT traffic exposes a lot of private information. Besides the existing goals (fingerprinting device and user behaviors), the traffic could possibly be used to fingerprint more CIoT applications that expose user privacy, such as the dialogue of smart voice assistants and automation rules [212] (e.g., IFTTT). Studies have shown that IFTTT is vulnerable to malware streams [212, 213].

E. Countermeasures

Almost all papers discussed in Section VI target gaining knowledge by passively analyzing CIoT traffic. On the other hand, some studies aim to defend against traffic analysis using traffic morphing, which prevents traffic patterns from being recognized/fingerprinted. Considering the limited computing power of CIoT devices, researchers try to save bandwidth when dynamically shaping the traffic [214, 215]. Furthermore, more up-to-date, perturbation-based traffic modification systems that employ Generative Adversarial Networks (GANs) are proposed [216, 217]. Meanwhile, attackers can also craft adversarial sample attacks to evade DL-based Network Intrusion Detection Systems (NIDS) [218]. Moreover, to protect the user's privacy but avoid the negative impact on the NIDS's performance, researchers adopt Differential Privacy (DP) techniques to shape the CIoT traffic [219, 220, 221]. A more efficient traffic shaping scheme that can be easily deployed in different CIoT scenarios (e.g., deployed on the smart hub, router, or device) deserves further exploration. We detail these countermeasures for traffic analysis in Appendix A for readers who may be interested.

VIII. CONCLUSION

We surveyed 310 papers about traffic analysis in the CIoT security and privacy field from 52 conferences and journals with high reputations. By summarizing the process of CIoT traffic analysis into four steps, new characteristics of CIoT traffic are identified, especially the complexity of traffic collection and processing. Next, we looked into the five application goals of current studies and concluded their contributions and deficiencies based on the CIoT traffic analysis process. Compared to general traffic analysis (like website fingerprinting), the heterogeneous CIoT network architectures, application scenarios, and device types indeed bring several new challenges in traffic analysis. Finally, we summarized the challenges and pointed out future directions, including the CIoT traffic analysis process, new applications, and countermeasures. In conclusion, with the widespread research of AI technology and emerging new applications of CIoT, traffic analysis, which is valuable for security and privacy, has wide prospects and research opportunities.

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