This article has been accepted for publication in IEEE Internet of Things Journal. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2022.3150363

Recent Advances on Federated Learning for Cybersecurity and Cybersecurity for Federated Learning for Internet of Things

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***Abstract*—Decentralized paradigm in the field of cybersecurity and machine learning (ML) for the emerging Internet of Things (IoT) has gained a lot of attention from the government, academia, and industries in recent years. Federated cybersecurity (FC) is regarded as a revolutionary concept to make the IoT safer and more efficient in the future. This emerging concept has the potential of detecting security threats, taking countermeasures, and limiting the spreading of threats over the IoT network system efficiently. An objective of cybersecurity is achieved by forming the federation of the learned and shared model on top of various participants. Federated learning (FL), which is regarded as a privacy-aware machine learning ML model, is particularly useful to secure vulnerable IoT environment. In this paper, we start with background and comparison of centralized learning, distributed on-site learning, and FL which is then followed by a survey of the application of FL to cybersecurity for IoT. This survey primarily focuses on the security aspect but it also discusses several approaches that address the performance issues (e.g. accuracy, latency, resource constraint and others) associated with FL which may impact the security and overall performance of the IoT. To anticipate the future evolution of this new paradigm, we discuss the main ongoing research efforts, challenges, and research trends in this area. With this paper, readers can have a more thorough understanding of FL for cybersecurity as well as cybersecurity for FL, different security attacks, and countermeasures.**

***Index Terms*—Machine learning, Cybersecurity, Federated learning, Federated cybersecurity, Data offloading**

I. Introduction

With the explosive rise of connected devices like personal digital assistants (PDAs), IoT, wearable medical devices, and others, an unprecedented amount of data is being generated every fraction of time. The immense volume of data has provided a better opportunity to utilize the machine learning (ML) model in general and deep learning (DL) in numerous domains [1]. Today ML has made its way even to our everyday lives. From the small hand-held devices, IoT sensors, and cyber-physical systems (CPS) to big companies like Facebook, Google, Amazon, Netfilx have been applying ML for their applications and services. Amazon Web Services, Google Cloud, and Microsoft Azure just to name but a few are some popular ML services [2], where models can be deployed and used at scale. ML has been inevitable not only to improve user experience, business modeling but also to detect cyber threats and cyber-attacks and prevent them. Today's world heavily exists on data and maintaining its integrity and privacy is of utmost priority. Sensitive data related to individuals, organizations, and governments needs to travel from one point to another through a communication link. Traditional methods of combating cybersecurity issues mostly protect devices only after the occurrence of specific types of attacks. However, the types and patterns of attacks in today's cyberspace have changed drastically. Attacks using polymorphic viruses keep on changing their signature and are difficult to detect and predict. So, the ML approach of detecting and predicting threats, anomalies, or any kind of security breach in cyberspace and taking corresponding countermeasures is gaining so much attention in recent years. Forming a centralized learning model by sharing local training data has already proven to improve the learning model's performance [3].

There are multiple models in practice for ML based cybersecurity each with its advantages and disadvantages namely centralized, decentralized and federated [1]. FL model for cybersecurity is a recent addition among these models. We discuss all these models in the subsequent sections. Moreover, FL has been explored for its applicability in several areas such as smart city [4], healthcare [5], recommender system [6], wireless communication [7], edge network [8], electric grid [9], vehicular ad-hoc network [10] and many more. FL framework inherently supports security and privacy (compared to the centralized learning framework) as data generated in an end device does not leave the device. The useful device data is used locally to train the learning model running on the device in a distributed manner. Only the updated parameters are exchanged between an end device and the cloud server. However, this approach still exposes several security threats. So, this survey primarily focuses on the security aspect of the application of FL. FL framework offers promising potential to improve security and privacy, but for the success of it, the issues that hinder the performance of FL must be addressed. In this regard, we also discuss existing works that address such issues such as the accuracy of FL model, latency of communication, data distribution, and resource constraint of distributed devices.

Due to the increasing complexity of software and communication interfaces, IoT and cyber-physical devices are

Manuscript received Day Month, Year.

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This research was funded in part the DoD Center of Excellence in AI and Machine Learning (CoE-AIML) at Howard University under Contract Number W911NF-20-2-0277 with the U.S. Army Research Laboratory and in part by the U.S. National Science Foundation (NSF) under the grant CNS/SaTC 2039583 and 1828811 as well as in part by NNSA MSIPP Grant.

more vulnerable to various kinds of attacks. Cybersecurity breaches in such systems are likely to incur several privacy and security issues. Appropriate safety measures and effective and robust cybersecurity solutions are mandatory to combat any threats or attacks. Below, we outline some common security risks associated with IoT and CPS where machine learning algorithms rely on data collected from such IoT/CPS systems.

Attacks on IoT/CPS devices: Hackers can easily crack the passcode of devices with a brute force attack and manipulate bluetooth connectivity of such devices to leak private information, manipulate data and/or gain control.

Attacks on Cloud-Based Networks: IoT and cyber-physical systems need to process a huge volume of data stored in the cloud frequently. These devices use different mediums of communication such as Wi-Fi, cellular network, etc. to send and receive data to and from the cloud. These communication mediums are vulnerable to attackers and attackers in the middle might intercept and forge the data being exchanged.

Malware: Like any other connected device, IoT and cyber-physical devices are also susceptible to malware attacks.

Vulnerable sensors: IoT and CPS devices are equipped with a wide range of sensors to monitor and support the systems. These sensors are vulnerable enough to be attacked by adversaries to cause security and safety threats. Even major sensors like global positioning system (GPS) signal, Light Detection and Ranging (LiDAR) signal, Inertial Measurement Unit (IMU) data, and so on can be compromised cause serious threats to the devices.

Network attacks: Every device or endpoint in IoT and cyber-physical systems is a part of the network attack surface. Attackers can target the endpoints of the network and gain access to the network to control and compromise the whole system. Protocols like WiFi, Bluetooth, and GSM allow external devices to connect and communicate with various sensors. These protocols contain bugs and are vulnerable to be exploited by attackers.

Firmware attacks: In this form of attack, an attacker provides a malicious firmware update to a device by which he/she can get direct access to the whole system.

There are already several surveys (e.g. [1], [11]–[15]) which reviewed FL and highlighted its taxonomies, methods, advances, applications, challenges, and more. However, our work is different from others since it presents the study about FL for cybersecurity and cybersecurity for FL in CPS/IoT environment. Successful adoption of FL for IoT environment hugely depends on several performance metrics which are also reviewed and presented in this paper. To combat various kinds of cyberthreats, an intrusion detection system (IDS) and intrusion prevention system (IPS) should be in place. Such systems must learn about the existing cyberthreats globally and even need to be proactive to detect and predict new and emerging threats. Collaborative learning framework of FL is suitable for such tasks. To evaluate security solutions properly, there have been significant efforts to create real datasets for more than two decades. This survey also highlights such works and discusses most of the datasets used by the research presented in this survey. We also discuss some popular datasets used in federated setting to evaluate federated model's performance. A shift in this new architecture of learning, has introduced some novel attacks such as poisoning and reverse engineering and we also discuss research works that address these attacks. In this survey, in addition to discussing several recent research works in the field of FL, we also present ML algorithms and technologies applied by those works. The aim of this survey is to assist readers to choose a particular research direction with overall information. Specifically, the main contributions of this paper include:

- We present a detailed study on federated models for machine learning and cybersecurity by categorizing them into two parts. The first part discusses the FL and its application in cybersecurity and the second part discusses cybersecurity for FL. Our study mainly focuses on IoT/CPS environment.
- As successful adoption of federated models for IoT environment hugely depends on several performance metrics. We also present those metrics, challenges associated with them and the potential solutions in this paper.
- We also present and discuss datasets used by the surveyed articles to evaluate their model's performance.
- We have also presented cyberattacks such as parameter poisoning and reverse engineering in FL.
- We summarize security attacks and countermeasures and the addressed performance issues in federated models for IoT networks in a tabular form for a side-by-side comparison.
- We present a discussion of research challenges, open problems, and recommendations for federated models that are needed to be addressed to realize their full potential.

The remainder of this article is organized as follows. In Section II, we discuss and compare different types of machine learning models. Existing recent works related to using FL as a tool to secure IoT environments and that related to making FL framework secure are discussed in Section III. Some research efforts to address the issues that affects the performance of FL are presented in Section IV In Section V we highlight ML algorithms, technologies, frameworks and and in Section VI, we discuss datasets used by the surveyed research respectively. Some open challenges and future research directions in FL for the IoT domain are presented in Section VII. Finally, we conclude our survey work in Section VIII. Full forms of various abbreviations are given in Table I.

II. Overview of Federated Learning and Federated Cybersecurity Model

In this section, we first present a brief overview of different types of learning models and then elaborate more on FL along with its challenges. Finally, we present a federated cybersecurity model useful to protect the FL framework.

A. Typical Types of Learning Models

Approaches to combating cybersecurity issues have been changing continuously with the needs. To cope with the

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TABLE I
ABBREVIATIONS AND FULL FORMS

Symbol	Full Form
CNN	Convolution Neural Network
GRU	Gated Recurrent Unit
SAE	Stacked Autoencoders
AWID	Aegean Wi-Fi Intrusion Dataset
MNIST	Modified National Institute of Standards and Tech.
Cifar10	Canadian Institute For Advanced Research dataset
LSTM	Long Short-Term Memory Networks
SVM	Support Vector Machine
VGG11	Visual Geometry Group
KWS	keyword spotting
NS3	Network simulator 3
DNN	Deep Neural Networks
DRL	Double Deep Q Learning
EV	Electric Vehicle
MLP	Multilayer Perceptron
KNN	K-Nearest Neighbor
SOHO	Small Office or Home Office
ADS	Anomaly Detection System
BC	Blockchain
RF	Random Forest
ECC	Elliptic Curve Cryptographic
IDS	Intrusion Detection System
SDN	Software Defined Network
NFV	Network Function Virtualization
WAN	Wide Area Network
DTN	Delay Tolerant Networking
IIoT	Industrial Internet of Things

unprecedented growth of heterogeneous connected devices and a tremendous volume of data and traffic generated by them and the development of sophisticated tools to create polymorphic malware and other threats, ML has been an integral part of cyber defense mechanism in recent times. This section discusses three different ML enabled models with their advantages and disadvantages.

1) Centralized Learning Model: This model uses cloud-centric architecture (e.g. [16]–[19]) where data sent from end devices is centrally stored and processed in the cloud. In the cloud, data is analyzed, features are extracted and then models are built on top of the stored data. Models are accessed by the end devices sending requests through an API. This approach offers significant advantages but carries some serious issues. One big advantage of this approach is that the cloud offers a huge repository so that storing huge volumes of data sent by all the clients will not be problematic. Another advantage is that the cloud is mostly equipped with high-performance servers. These benefits facilitate the building of better-trained models. Moreover, cloud services are best protected by service providers for any security breaches or attacks. Offering such great advantages, this approach has serious concerns over privacy, security, and latency. All the data needs to travel to the cloud through insecure communication links makes the data vulnerable to being hacked by adversaries. All the private data generated by the devices are stored in the cloud raises big privacy concerns. Further, the central authority or the cloud service provider has all the control over the model and data. Additionally, as data needs to travel to and from the cloud, latency and bandwidth costs could be big issues if the communication distance between device and cloud is high. The working model of centralized learning is shown in Fig. 1.

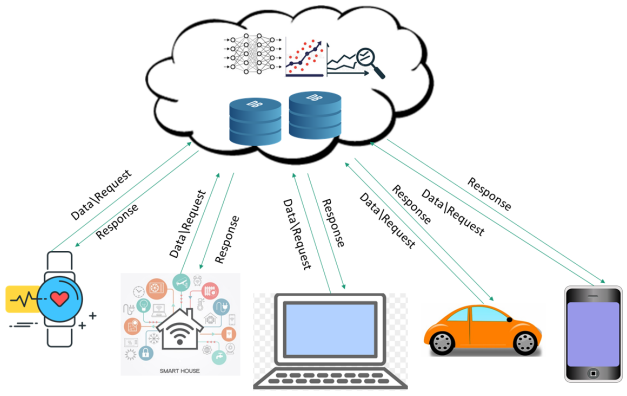

Fig. 1. Centralized learning model for Internet of Things

2) Distributed on-site Learning Model: In this approach of learning model, a generic or pre-trained model is distributed by the server to all the devices or clients beforehand. After this, each device personalizes the model with training and testing with local data and learns the data generation process. Such a learned model enables predictions and inferences from live-streaming data generated by the device [1]. The big advantage here is data generated by the device stays locally thus eliminating security, privacy, and latency concerns. The main downside of this approach is that IoT devices are relatively heterogeneous and weak in terms of memory, computation, and battery power. These devices are not suitable for the intensive computation required while using the model [20]. Further, the locally running model lacks global updates or knowledge about new and emerging security threats. The working model of distributed on-site learning is shown in Fig. 2.

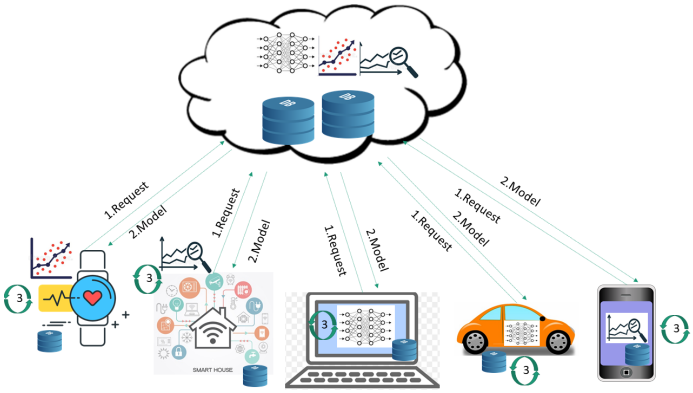

Fig. 2. Distributed on-site learning model for the Internet of Things

3) Federated Learning Model: It is a kind of distributed model but with the facilitation of global knowledge collected from all the distributed clients. Same as a distributed setting, a general or pre-trained model is distributed to clients initially.

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All the clients personalize the model locally with its local raw data. Clients perform ML tasks locally and send their parameters to the server. The server then aggregates all the updates received from the clients and performs ML tasks and finally distributes the updated model to the clients [11]. This is an ongoing process by which the clients are constantly provided with all the new and emerging global knowledge. The working model of FL is shown in Fig. 3. This learning model first formulated by [21] is as follows:

$$f(w) = \sum_{k=1}^{K} \frac{n_k}{n} F_k(w) \text{ Where } F_k(w) = \frac{1}{n_k} \sum_{i \in P_k} f_i(w) \quad (1)$$

In equation 1, $f_i(w)$ represents a loss function of prediction for input x_i to an expected output y_i with weight vectors w. K is the number of participants in the current learning round and $F_k(w)$ is the local objective function of k_{th} participant. For total number of samples n, n_k is the number of samples present locally in k_{th} participant. Similarly, P_k with $n_k = |P_k|$, is the partitioned assigned to k_{th} participant from whole dataset P.

In a typical FL setting, when a device downloads the current model parameters (weight) from the server first, it initializes the local model with the downloaded parameters, and then the local dataset is used to train the model. The parameters are optimized by minimizing the local objective function that uses stochastic gradient descent (SGD). The optimized parameters from all such devices are sent to the server where they are aggregated using FederatedAveraging algorithm [21]. This way the global model is updated and the learning takes place.

As raw data resides locally on the device and only ML parameters are sent to the server, FL ensures privacy of the raw data of clients and complies with privacy policies and/or regulations e.g. The European Data Protection Regulation "General Data Protection Regulation (GDPR)" [22]. Additionally, FL frameworks are also enriched with privacy-preserving techniques like differential privacy [23], secure multi-party computation (SMC) [24], homographic encryption (HE) [25] to send the ML parameters from clients to server securely. Despite presenting propitious potential, FL brings several challenges when it is applied with IoT. Here, we highlight some major challenges associated with FL for IoT.

1) Limited Device Memory: IoT devices constantly generate data during their operation. Due to their limited memory, when the batch size of data increases, training the federated model locally is not feasible. In a FL scenario, these devices might be dropped out or are forced to use a simple model to work with small batch sizes in the training phase [1].
2) Limited battery power: If the learning model is complex and the training data size is huge, IoT devices might be run out of battery power during the training phase.
3) Limited computing power: IoT devices, in particular, are limited to computing power. Due to this constraint, training the model locally by such devices may not be a feasible approach.
4) Vulnerability: We have seen an unprecedented growth of diverse sets of IoT devices in recent times. Some categories of IoT devices are vulnerable enough to be gain controlled by hackers. Such devices might produce malicious data and when such data is used to train the model, it might even affect the global or federated model.
5) Unreliable and limited availability: In FL, clients can drop out anytime. Clients might be dropped out by several factors like unreliable network connection, limited storage, computation power, and more. Moreover, the availability of clients depends on time and location. More clients might be available during day time compared to night time. Day and night time also differ by geographical location.
6) Stateless: Availability of clients depends on several factors and so the client does not guarantee repeated computation.
7) Anonymity and poisoning: Clients in FL are anonymous which makes it hard to differentiate between genuine or malicious clients. So, there might be a chance that the federated model might get poisoned by the involvement of malicious clients.
8) Non-Independent and Non-Identically Distributed (Non-IID) Data: The nature of local data on a device depends on its unique behavior and usage pattern and so the distribution of clients and data is non-uniform. The data of the same device might differ because of the change in location, time, and users.
9) Local training: Each client is limited to its local data. Non-enough data on a device might not be able to train and produce a good model.
10) Accuracy: Due to characteristics of FL like Non-IID data, stateless, local training, and resource constraint, the aggregated global model might not be as accurate as compared to centralized learning. Non-accurate global model in turn might affect the local model and as the chain reaction, the global model is again getting more

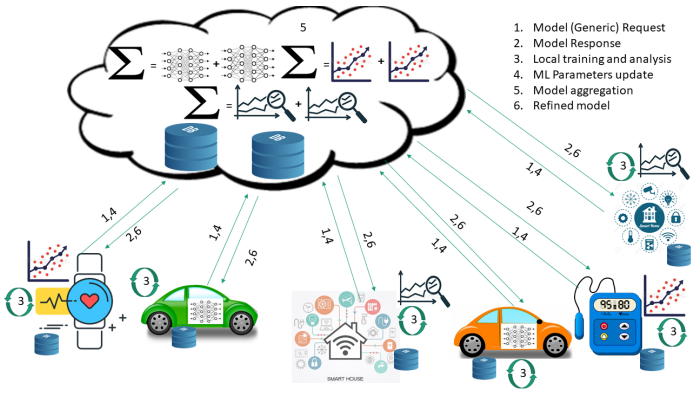

Fig. 3. Federated learning model for Internet of Things

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affected.

11) Communication overhead: The frequency of communication for a client with a server not only depends on factors like its characteristics, size, and quality of local data but also might be heavily influenced by other clients. Frequent communication with servers to keep the local model consistent with the global model increases communication overhead.

Since the first proposal of FL in [21], there have been several research to address challenges that existed in FL. For example, to reduce communication overhead by aggregating global model only when the global model's weight differs by some empirically selected threshold is proposed [26]. For a similar issue, a control algorithm to find global aggregation frequency was proposed in [27]. To mitigate the effect of non-IID data and improve the accuracy, a feature fusion approach by aggregating local and global model is presented [28]. To address a similar issue, [29] designed a federated multitask learning (FMTL) framework to forms clusters of clients based on the geometric properties of the FL surface with jointly trainable data distribution. Combining FL and data offloading, resource constraint issue other challenges of IoTs are addressed in [20]. Detecting sybil based parameter poisoning from the diversity of client updates in the distributed learning process and taking corrective measures is proposed in [30]. Several works [31]–[33] have proposed IDSs in FL setting that learn from global knowledge of threats and detect new and emerging cyberthreats. We discuss several recent works that address challenges and issues that existed in FL in section III.

B. Typical Types of Cybersecurity Models

Security is the fundamental requirement of today's digital world. An exponential rise of vulnerable heterogeneous IoT devices and furthermore communicating through a wireless medium, has widened the attack surface significantly. Wireless communication networks' standards and protocols are different but more vulnerable than wired communication networks. The mobile and distributed nature of the IoT devices exaggerates the security challenges even more. So, the security solutions designed for wired networks can not be directly applied to the wireless network. Similar to learning models, cybersecurity models for IoT environments can be categorized into three types as isolated devices level cybersecurity model, distributed cybersecurity model, and federated cybersecurity model (as shown in 4). We can think of these as cybersecurity models that provide security services working at different levels. Adopting one specific type of security model is insufficient so, an effective cyberdefence mechanism is likely to require the combination of such models working in place.

1) Isolated Devices Level Cybersecurity Model: This cybersecurity model works at the lowest level and concerns with providing security services to the end devices. Due to the heterogeneous nature of IoT devices, each category of devices might have specific vulnerabilities and security requirements. So, the device-level cybersecurity model needs to take care

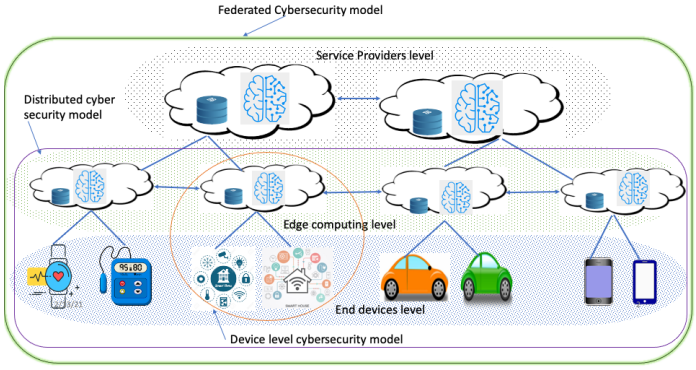

Fig. 4. Federated Cybersecurity Models for Federated Learning in the Internet of Things

of safeguarding the device against any malicious activity. From the basic security measures such as password setting, validating authentication, access control, it aims to validate each connection request and establish secure communication to the outside world. Device-level security also aims to validate the timely software updates and makes sure the update process is completely secure. Furthermore, it also aims to safeguard the device against malware attacks. Although device-level cybersecurity model intends to provide all the essential security measures, it is not sufficient to fully protect the system. Attackers use sophisticated tools and codes to generate new and polymorphic malware to attack the connected system. So, it necessitates the device-level security to be backed by machine learning models to learn and adapt based on the dynamic scenarios. It should be capable of taking defense mechanisms on any attacked or anomalous situations and allowing smooth device operations. However, most of the IoT devices are resource constraint which makes them incapable of running machine learning models. To deal with it, in an IoT network, a gateway node or edge node is typically employed for running ML-backed cybersecurity model and providing necessary security to all the end devices connected in the network.

2) Distributed Cybersecurity Model: A significant number of new cyber threats are being introduced every day. Learning from cyber attacks/threats from one IoT network is not sufficient. In a distributed network, edge nodes are geographically dispersed and are closest to the end devices or users. So, a distributed cybersecurity model aims to enable collaboration and cooperation among geographically distributed edge nodes to provide better security services. Based on the characteristics of the underlying IoT network, edge nodes among themselves may be distinctive for the specific security services they offered. If any edge node can not provide the intended service to a nearby device or user, it collaborates with other nodes at the same level to do so. Such collaboration facilitates to provide appropriate security solutions to combat emerging cyber threats/attacks in the real-time scenario.

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3) Federated Cybersecurity Model: It is a cybersecurity model which provides security and other services from the top level in the federated model based on the feedback from the bottom/device level (e.g., [34], [35]). IoT service providers participate in this level to provide the necessary services to their respective users or devices. Each user can access the respective services from its service provider. The edge node on a particular IoT network acts in the middle to ensure the necessary security and services are provided to its end users or devices. Each service provider is responsible to disseminate essential security services to all its distributed devices through edge nodes. In this security model, each service provider learns from all its devices and updates the security model accordingly. Furthermore, these independent service providers also collaborate themselves to make dynamic defense strategies/solutions to combat against possible attacks/threats. In the immediate lower level, if edge collaboration could not provide a security solution in real-time, a particular edge node reaches out to its service provider. The service provider then provides the necessary security solution or collaborates with other providers to do so.

4) Federated Learning and Federated Cybersecurity: The existing approach of the federated cybersecurity model provides security solutions to IoT applications through communicating and collaborating at different levels as needed (e.g., [36]–[38]). However, the traditional way of exchanging data/information within the same level and/or between different levels can pose privacy and security concerns (e.g., [39]–[41]). Federated learning has been emerged as a solution to exchange data/information in a secure and privacy-preserving way. A Federated cybersecurity model accompanying FL to collaborate and exchange any information at any level offers a huge potential to make the IoT network safe and secure. Most of the federated cybersecurity approach utilizing FL as a cyber-defense mechanism primarily focused on securing IoT networks considering a single global model offered by a single service provider. However, this approach can easily be extended to a collaborative scenario involving multiple global models maintained by different service providers. only a few research have worked toward creating a sense of federated security model utilizing multiple global models. We present a survey of several research efforts towards creating federated cybersecurity models for IoT network using FL in the next section.

III. Recent Advances on Federated Learning for Cybersecurity and Cybersecurity for Federated Learning

The focus of this work is to survey several existing works since 2015 toward cybersecurity particularly for IoT environments. The addressed issues by those works and the environments where they are implemented or tested are given in Table II. In recent times, a significant number of research works for addressing security in the IoT networks have been shifted toward applying FL. The framework of FL inherently supports privacy, to some extent security, and latency as only updates are required to transmit but these are costlier to achieve in centralized learning. Distributed learning addresses these issues but lacks global knowledge of collaborative learning. There are some downsides of FL in IoT networks too like heterogeneity of devices, resource constraint, non-IID data, accuracy, and others. Mainly, most of the FL surveyed works address security and privacy issues but there are several works that also address issues like latency [26], [42]–[47], resource constraint [20], [27], [48]–[51], accuracy [28], [47], [52] and non-IID [28], [29], [45]. All these issues are somehow dependent on each other and improving one issue should not affect the others. Some works have considered all these issues while others addressed the only subset of these. We will discuss some of the contributions made to alleviate such issues present in FL. Although FL in the IoT environment is our primary focus of study, some recent works we studied are proposed and tested in the distributed learning setting. We have also mentioned those works considering their usefulness to secure IoT environment and are easily extensible to FL setting.

We have summarized surveyed works into two groups. In one group, we discuss existing works related to FL as a tool for cybersecurity and in the next, we present works based on cybersecurity need for FL. FL as a solution to different types of attacks and FL as a target to different potential cyberattacks are highlighted in Fig. 5. A collaborative approach of identifying and learning different types of attacks can be highly effective to mitigate daunting threats like intrusion, Dos/DDos, anomaly, and others. On the other hand, before utilizing FL for real applications, the emerging attacks typical to FL are required to be addressed.

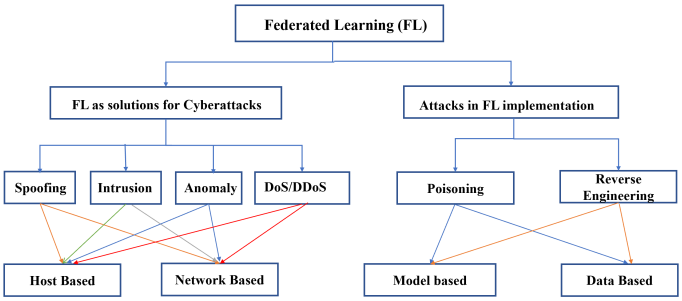

Fig. 5. Federated Learning (FL) as a security solution to different attacks and novel attacks present in FL

A. Federated Learning for Cybersecurity

Security, privacy, and trust have been extensively studied in the literature in the context of cyberspace. However, this survey is particularly focused on cybersecurity for IoT environments in the FL setting. IoT environment is more vulnerable to different types of cyberattacks so, a collaborative learning framework of FL only by sharing the model update can be an effective solution to enhance security and privacy. A timely learned and shared global knowledge of different types of cyberattacks like spoofing, intrusion, anomaly and DoS/DDoS

TABLE II
ADDRESSED ISSUES BY SURVEYED WORKS

Addressed Issues	References	FL	Domain
Security,IDS, IPS	[53]	✗	Smart home
Security, DDoS Resiliency	[54]	✗	IoTs environment
Security, IDS	[3]	✓	IoT network
Malware classification	[55]	✓	Edge devices
Security, IDS	[56]	✓	Network environment
Security	[57]	✗	IoTs environment
Security	[58]	✗	IoTs environment
Security, IDS dataset	[59]	✗	IoT and IIoT
Security,IDS dataset	[60]	✗	-
Security	[61]	✗	IoTs environment
Security, IDS	[62]	✗	VANET
Security, IDS	[63]	✗	Network
Security, IDS	[64]	✗	Network environment
Privacy, Security, IDS	[32]	✓	CPSs
Security, ADS	[65]	✓	SOHO IoTs
Security, ADS	[33]	✗	Smart city IoT
Cyberattacks	[66]	✗	IoTs, CPSs
Cognitive cybersecurity	[67]	✗	CPS-IoT Enabled Healthcare
Privacy, integrity	[68]	✓	Edge devices
Security, Sybil based poisoning attack	[30]	✓	Edge network
IoT Mirai botnet attack	[69]	✗	IoTs devices
Reliability, Security	[70]	✗	IoTs network
Security, Audit	[71]	✓	Edge network
Security, Trust	[72]	✗	IoTs network
Security	[73]	✗	IoTs network
FL operation, Security	[74]	✓	Overall FL framework (IoTs, Edge cloud, Regional Cloud, Core Cloud)
Privacy, Security, Latency	[42]	✓	IoT edge computing (Connected vehicles)
Jamming attack detection and defense	[75]	✓	UAV
Security, Privacy Throughput, Latency	[43]	✗	IoT network
Privacy, Security, Communication overhead, computational cost	[44]	✗	Fog-based IoT
Gradient sparsification, Accuracy	[76]	✓	IoT edge computing
Security, Intrusion, Privacy, IDS	[31]	✓	IoT devices
Privacy, IDS	[77]	✓	Edge devices
Privacy, Latency, Non-iid	[45]	✓	IoT network
Latency	[46]	✓	IoT network
Learning speed, Accuracy	[52]	✓	Edge devices
Increased accuracy, Convergence process	[28]	✓	Edge devices
Communication, Accuracy	[47]	✓	IoT environment
Efficient communication and training	[26]	✓	IoT environment
Resource constraint, Global aggregation frequency	[27]	✓	IoT environment
Security, Resource constraint	[48]	✗	IoTs environment
Resource constraint	[20]	✓	IoT edge computing
Resource constraint	[49]	✓	WAN
Resource constraint	[50]	✓	IoT edge computing
Privacy, Latency	[78]	✓	Edge network
Non-iid, Accuracy	[29]	✓	Edge network
Resource demand, Scarcity of relevant data, Security, Latency	[79]	✓	IoT Edge network
Privacy, Security	[80]	✓	IIoT
Privacy, Security, IDS, Accuracy	[81]	✓	IoT environment
Security, Data collaboration	[82]	✓	IoT environment
Privacy, Security, Reliability	[83]	✓	IIoT environment
Safety, Resiliency Accuracy, Privacy, Latency	[84]	✓	IIoT environment
Security, IDS, Communication	[85]	✓	IIoT environment

facilitates building and enhancing cyberdefence models and mechanisms accordingly. So, FL has a huge potential to secure cyberspace effectively both in the device as well as network level. Application of FL as a solution to mitigate possible threats is depicted in Fig. 6.

In recent times, cyberspace has been more vulnerable due to the presence of unprecedented growth of heterogeneous sensor devices. IDS and anomaly detector backed by ML has become mandatory to detect and combat intrusions and anomalies in today's gigantic cyberspace. In literature, differ-

This article has been accepted for publication in IEEE Internet of Things Journal. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2022.3150363

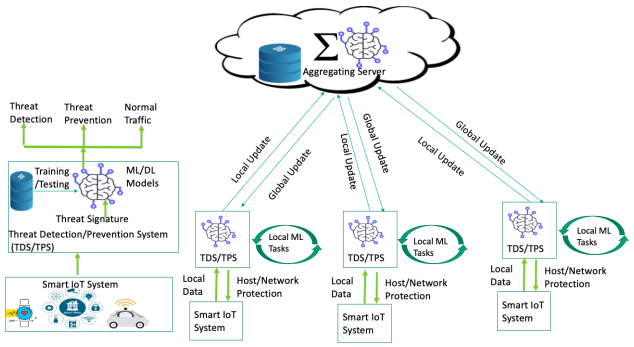

Fig. 6. FL as a solution to mitigate possible threats in IoT network.

ent approaches (e.g. [32], [64], [65]) using varieties of ML algorithms (e.g. CNN, NAR, Q-learning) have been examined to design IDSsIPSs and those are tested against several benchmarked datasets for its performance. Majority of the efforts dedicated to designing FL based security solutions primarily focused on the accuracy of the security model only without considering other important performance metrics. We cover FL works addressing performance issues in the next section.

Rahman et al. [31] proposed a FL based self-learning IDS to secure IoT environment. A bench-marked dataset (NSL-KDD) consisting of normal traffic and several attack types was first distributed over the IoT devices and then ML based IDS model was trained and tested locally. The model updates were sent and aggregated following the conventional FL operations. The proposed system achieved accuracy close to the centralized learning approach. FL approach was successful to create a self-learning IDS by which end devices were successful to detect attacks that were not presented in their local dataset. The advantage of such FL based IDS is that in a real application scenario, IDS can be capable to detect intrusions not generated previously by its own traffic. The downside of the proposed approach is that it was experimented within a significantly small IoT network environment and except accuracy, other performance metrics were not considered.

In [84], a collaborative IDS is developed as smart "filters' by deploying at IoT gateways in each sub-network. DNN of each filter is trained with a local database housed in sub-network and such learned models from the filters are collected and aggregated in a central server. Each filter supplemented by global knowledge is capable of detecting and preventing real-time cyberattacks. The performance of the proposed model was tested with multiple benchmarked datasets and it outperformed several baseline ML models in FL and centralized learning settings in terms of detection accuracy, network traffic, privacy, and learning speed. Despite the improved performances in several aspects, this approach is useful against known attacks only.

A robust FL based IDS using a generative model was envisioned in [85]. FED-IIoT, a FL based architecture for detecting malwares used generative adversarial network (GAN) and Federated Generative Adversarial Network (FedGAN) algorithms in the participant side to generate adversarial data and injects them into the dataset of each IIoT application. On the server side, a robust collaboration of trained models was ensured by incorporating a defense mechanism to detect and avoid anomalies while aggregation. The proposed model demonstrated higher accuracy compared to existing solutions and allows secure participation and efficient communication among participants in the IIoT environment.

With similar objective, work [32] designed an ML based IDS model to detect threats in industrial CPSs environment. The designed IDS model was further extended as a FL framework to allow multiple industrial CPSs collaborate to build a comprehensive IDS. Authors compared the effectiveness of the proposed model with state-of-the-art schemes through extensive experiments on real industrial CPS dataset. For ensuring security and privacy of the federated model parameters, authors incorporated paillier cryptosystem based secure communication protocol for the federated IDS. The advantage of this work is that it makes FL secure against the man-in-the-middle type attacks.

Aiming to identify the most critical cyberattacks in a smart home environment, [53] first highlights attack surfaces and prepares three test cases (to test confidentiality, authentication, and access control) to launch different types of cyber security-based attacks. An IPS is then designed and tested against the same attacks to verify the resiliency of the affected system.

In an effort to detect cyberattacks in a larger IoT network, a ML based network intrusion detection system (NIDS) capable of monitoring all the IoT traffic of a smart city in a distributed fog layer was proposed in [33]. The proposed model performed well to detect attacked IoT devices at distributed fog nodes and and alert the administrator accordingly. The NIDS model was evaluated against UNSW-NB15 dataset [86] and the model demonstrated the classification accuracy of 99.34%. Authors claimed their approach as unique stating that the NIDS model learns with normal traffic and can detect malicious behavior in the future.

Extending the traditional FL model, Sun et al. [3] proposed a segmented FL framework to detect intrusion for large-scale networked LANs. This approach is different from a traditional FL model that works on collaborative learning based on a single global model. The proposed approach instead keeps multiple global models where each segment of participants performs collaborative learning separately and also rearranges the segmentation of participants dynamically. Moreover, these models interact with each other to update parameters as per the various participants' LANs. The authors employed three types of knowledge-based methods for labeling network events and train a convolutional neural network (CNN) using a dataset. The model was trained and tested using a dataset consisting of using two months' traffic dataset of 20 participants' LANs and obtained a high validation accuracies. The advantage of the segmented FL framework is that it performed better to detect intrusion in LANs compared to the traditional FL approach of using a single global model.

A collaborative IDS (CIDS) to detect abnormal network behavior in the whole VANET was proposed in [62]. The

CIDS used deep learning and SDN controller approach to train a global IDS that can work in both IID and non-IID situations. Instead of directly exchanging sub-network flows, multiple SDN controllers were employed to train global IDS jointly for the entire network. The model was built and tested using KDD99, NSL-KDD datasets to validate the efficiency and effectiveness of the CIDS for VANETS. The main highlighting feature of the proposed approach is that the CIDS is effective to detect intrusion in the entire VANET and not just limited to the local sub-networks like other approaches.

To alleviate Wi-Fi network privacy concerns, a federated deep learning model [77] was built and tested using AWID. The proposed model used a specialized deep learning neural network called Stacked Autoencoders (SAE) to capture a compressed representation of anomalous observations. To identify the new threats, the federated model learns from the new observations and updates the local and global models. The result obtained was compared with the classical deep learning model and claimed that the FL model was more effective in terms of classification accuracy, computation cost, and communication cost. This work is different than others to use a specialized DNN which facilitates compression of model parameters which mainly benefits to reduce communication latency.

To deal with the emerging sophisticated polymorphic threats, a security solution needs to be proactive to identify unforeseen and unpredictable cyberattacks. In an attempt to design such a solution, Rege et al. [64] extend IDS to offer temporal prediction of adversarial movement. The proposed approach used four predictive models namely nonlinear autoregressive (NAR) neural network, NAR neural network with exogenous input (NARX), NAR neural network for multi-steps-ahead prediction, and autoregressive integrated moving average (ARIMA) and compared the results over two dataset collected at different locations. The research was able to identify five advanced persistent threats' trends - there will be more attacks, more obfuscation, continued false attribution, greater shifts from opportunity-based attacks to more targeted attacks, and more damage ranging from data manipulation to data encryption or deletion.

Motivated by the similar need, article [63] presented several experimental approaches to identify the best algorithm to design dynamic IDS that could effectively detect and predict intrusions at both host level and network level. Authors first experimented with various DNNs against publicly available benchmark malware dataset (KDDCup 99) by choosing optimal network parameters and network topology for DNNs. The well performed DNNs are then tested with other malware datasets NSL-KDD, UNSW-NB15, Kyoto, WSN-DS and CICIDS 2017 to set the benchmark. A similar approach was followed to identify well performed classical ML classifiers and to compare its performance with DNNs. The performance evaluation demonstrated that DNNs outperformed classical machine learning classifiers and finally, authors utilized the better performed DNNs to design a highly scalable and hybrid DNNs framework called scale-hybrid-IDS-AlertNet. The proposed IDS could not only monitor real time network traffic and host-level events effectively, but also proactively alert possible cyberattacks.

A federated self-learning anomaly detection and prevention system that is capable of detecting and preventing emerging and unknown attacks in IoT network (DÏoT) was proposed in article [65]. Without human intervention, DÏoT builds device-type-specific communication profiles which are eventually used to detect anomalies in devices' communication behavior. Security gateways were employed in such a way that each gateway is assigned to monitor the traffic of one particular device type. The collected traffic data was then used to train the local model of each gateway and the model parameters of the training were sent to an IoT security service for aggregation. IoT security service had been used as a repository of device-type-specific anomaly detection models which in the later stage also used to aggregate all the updates received from security gateways.

In [56], Pang et al. proposed a learning agent-based Federated Network Traffic Analysis Engine (FNTAE) for detecting real-time network intrusion. To detect abnormal traffics as a result of new attacks, the proposed model made use of an analysis engine powered with an incremental learning agent to capture attack signatures in real-time. FNTAE demonstrated well compared to centralized analysis system however, it is useful only to combat against the known attacks.

To secure an IoT environment, some works have followed other approaches too. Work presented in [57] proposed Man-In-the- Middle-IoT-Computing tool (MIMIC) which utilizes the man-in-the-middle attack concept to deploy MIMIC as a fog computing agent for IoT networks. MIMIC is deployed at the edge node of the IoT network to be able to sniff, capture, and replay all the incoming packets from IoT devices. MIMIC then creates a virtual layer for holding the virtualization of all the sensing devices and the remote users are allowed to query only on the virtual space disabling the direct access to physical devices. In [58], Zarca et al. proposed a novel approach of utilizing SDN and NFV to deploy IoT honeynets to distract cyberattackers and make IoT system secure. Administrators of IoT system can deploy IoT honeynets as a service through high-level security policies defined over SDN controller and NFV Management and Network Orchestration by replicating the physical IoT architecture on a virtual environment as VNFs. The model experimented in a testbed of H2020 EU project premises and it was successful for filtering, dropping, and diverting the network traffic dynamically, and adapting the network behavior according to the new deployed vIoTHoneyNets (virtual IoT honeynet) needs.

There have been other significant research to study cyberattacks and build corresponding cyberdefense mechanisms that using different approaches, utilizing varieties of databases, API, platforms, frameworks, and ML algorithms. For example, a malware classification prototype accompanied by decentralized data collection and sharing using the FL model approach was developed in [55]. Dataset of 10,907 malwares obtained from virustotal api was used for training and testing

the model. Authors used SVM and LSTM machine learning algorithms in a federated setting to achieve better results on the classification of malwares. A framework called DRAFT is developed in [54] by integrating other frameworks and tools to improve the resiliency of end-to-end IoT platform against cyberattacks. The proposed model was integrated in IoT platform and tested against five known simulated cyberattacks using Fed4FIRE+ federated testbeds and demonstrated the increase in cyberattack resiliency for tested IoT platform. An adaptive federated reinforcement learning was proposed in [75] to combat jamming attack in unmanned aerial vehicles (UAVs). The proposed model used model-free Q-learning and CRAWDAD dataset and learned jamming defense strategy in a newly explored environment. Paper [66] studies cybersecurity in the context of Big Data IoT and CPS. Cybersecurity issues and vulnerabilities associated with CPS were investigated and analyzed to pinpoint possible cyberattacks. The authors also presented technical approaches to mitigate those attacks. In [67], Abie et al. proposed a four-layer architecture of cognitive cybersecurity to combat against dynamic and adaptive attacks in smart CPS-IoT enabled healthcare environments. The presented conceptual architecture aimed to mimic the cognition behavior of humans to anticipate and respond to new and emerging cyber threats in the smart healthcare domain. In another work of providing cybersecurity for IoT devices [48], authors presented an approach of incorporating a trusted Network edge device (NED) developed in [87] as a proxy service for IoT communication. To protect IoT devices, users can set up security solutions and policies easily and efficiently for multiple IoT gateways and end devices at once via NED. The proposed approach is experimented in corporate scenario in VTT Oulu premises. A work presented in [73] highlights several hardware-assisted techniques employed in the literature that can be applied to add another layer of protection to combat cyberattacks in the IoT domain. The paper also explored the hardware solutions with respect to cost, performance, security, and presented challenges to adopt in real scenarios.

To improve security and reliability in an IoT environment, a reliable and efficient adaptation of cluster techniques (REACT) was presented in [70]. In REACT, an effective cluster head selection algorithm and energy balanced routing algorithm were proposed and simulated with estimated parameters against existing protocols HEED and LEACH comparing throughput, network lifetime, energy remaining, and reliability. The paper also presented a strategy of a cyber-hacking technique of selecting an attack point to improve the cybersecurity design. With the aim of facilitating the design of an effective IDS and evaluating it properly, some works have dedicated efforts to fill the gap of the availability of benchmarked intrusion dataset to test IDSs-enabled IoT systems. The work presented in [59] proposed a new data-driven IoT/IIoT (TON_IoT) dataset containing Telemetry data of IoT/IIoT services, Operating Systems logs, and Network traffic of IoT network, collected from a realistic representation of a medium-scale network at the Cyber Range and IoT Labs at the UNSW Canberra (Australia). TON_IoT also contains label and type features indicating multiple classes and sub-classes suited for IoT/IIoT applications for multi-classification problems. The features of the dataset were compared with other existing datasets to show its superiority. In another example, [60] produced one of the most popular intrusion dataset named CICIDS2017 which contains an important set of features and meets real-world criteria. The produced dataset is fully labeled containing more than 80 network traffic features and meets all the required criteria with common updated attacks such as DoS, DDoS, Brute Force, XSS, SQL Injection, Infiltration, Port scan and Botnet.

In this section, we discussed several existing approaches to design cybersecurity models particularly for IoT environments and in FL setting. Many ML algorithms, blockchain, network virtualization, SDN, clustering approaches, and others have been explored aiming to design an efficient cyber defense mechanism to detect and prevent intrusion, anomaly, Dos/DDoS, and other attacks in different types and sizes of IoT networks.

B. Cybersecurity for Federated Learning

We presented several works discussing FL as an effective solution for different kinds of security and privacy issues. However, this new learning architecture has invited some novel kinds of attacks. In the FL setting, although the data resides locally in end devices and only ML parameters are exchanged between client and servers, it is still vulnerable to different kinds of attacks. We first discuss different types of attacks to FL and then present the mitigating strategies proposed in research.

Parameter poisoning (or model poisoning) and reverse engineering ML attacks are some serious threats in FL and are an active area of research [e.g. [30], [88], [89] [90], [80]]. The typical attacks in FL can be data based or model based (as shown in Fig. 5) which can be performed by forging local data of end device(s) or the model parameters on client or server side. How an attacker may perform different attacks in FL is shown in Fig. 7. As depicted, an attacker may control IoT device/network to compromise local data and/or local ML tasks to generate poisoned model. In other scenarios, an attacker may perform man-in-the-middle attack to forge the model update in transit or just to overhear communication to reveal the privacy of a user.

Attacks in FL can not only degrade the quality of the learning model but also expose the privacy of users. An adversary can reveal the privacy of a user by spoofing on model updates sent by the user's device. Moreover, if the adversary gains control of the aggregating server, he/she can get comprehensive knowledge of the history of update parameters of devices and the structure of the global model. With these information, adversaries can reveal the privacy of devices through reverse engineering.

With access to the model updates, some works demonstrated generating pictures that look similar to the training images using generative adversarial network (e.g. [91], [92]). Extending the leakage of private information to the next level, Zhu et

This article has been accepted for publication in IEEE Internet of Things Journal. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2022.3150363

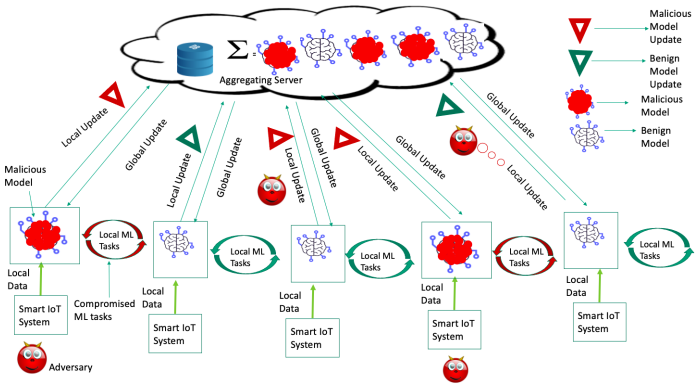

Fig. 7. Attack scenarios in FL.

al. [93] demonstrated that an attacker can completely steal the private training data from the shared model updates in a few iterations. To achieve this, authors first generated a pair of dummy inputs and labels and which were used to generate dummy gradient following the common training process. Rather than optimizing weights, they optimized dummy inputs and labels so as to minimize the distance between dummy gradients and real gradients and were successful to reveal the training data completely. Further, with the full control of central server, adversaries might forge the global model which in turns might affect the local model of the end devices. In effect, aggregating local updates of such models might degrade the quality of the global model significantly. Even if adversaries do not have control over end device or server, the model parameters might still be forged while in transit between client and server.

On the other side, FL is also vulnerable to data poisoning and model poisoning attacks performed through end device(s). If an adversary gains control over an end device, he/she may forge the local data and/or forge the model update during local model training process with intention of creating a biased model. The parameters of the biased model in turn might affect the quality of global model. This problem gets even worse in case of byzantine problem [94] and sybil attack [95]. A survey presented in [14] categorizes and discusses threats to FL and presents future research directions to create robust FL framework.

Label flipping attack is one of the most common data poisoning attack where the labels of training examples of one class are changed to another class (keeping features of the examples unchanged) to force the model predict incorrect label. Fung et al. [30] demonstrated label flipping attack by flipping the label 1s in the training dataset to label 7s and making the model incorrectly classify 1s as 7s. In other form of data poisoning attack, an attacker may change individual features of the original training dataset to plant backdoors into the model [14]. The general approach behind the backdoor attack is to replace the global model with the attacker's model and force it to mis-predict on a specific sub-task, e.g., compelling an image classifier to misclasify green cars as frogs [96]. Once the estimate of global model's state is perceived, an attacker can replace the model with simple weight re-scaling operation [97]. Bagdasaryan et al. [96] exhibited backdoor attack by injecting certain pattern to the data and altering the label to the desired target so as to mislead the global model. The the attack scenario consisted of one or more malicious participants which train on the backdoor data and then share the model update to the server for aggregation.

Data poisoning ultimately poisons the model update however, an attacker may directly manipulate training process without poisoning training data and it is to be noted that this form of model poisoning is regarded as more effective than data poisoning. In [88], Bhagoji et al. demonstrated using model poisoning attacks considering a single, non-colluding malicious agent with the adversarial objective of causing the FL model to misclassify a set of chosen inputs with high confidence. To make the targeted misclassification effective, authors employed malicious agent's update boosting as well as alternating minimization strategy to alternately optimize the training loss and the adversarial objective. In another example, Blanchard et al. [98] exhibited model poisoning considering omniscient attack (adversaries with aware of good estimate of gradient) where adversaries send opposite update vector by multiplying with negative constant to reverse the direction of gradient descent and degrade the model performance. Furthermore, Baruch et al. [99] demonstrated that model poisoning through Byzantine-attack is still possible in non-omniscient attack scenario by introducing even a small but well crafted changes on gradient.

Byzantine-tolerant learning in the distributed setting has been addressed in some works (e.g. [100], [101], [102], [92], [103]) where most of them assume participant's data is i.i.d, unmodified and equally distributed. However, in FL, data distribution is different and there solutions is not fully applicable. Bagdasaryan et al. [96] exploited the solutions presented in [101], [92] and [103] and was able to partially mitigate the attack but that is also at the cost of global model's accuracy. To address model poisoning, Fung et al. [30] first demonstrates the FL's vulnerability against sybil based poisoning attack through experiment and presented a FL model FoolsGold that identifies such attack based on the diversity of client updates in the distributed learning process. This model even works effectively in case sybils compromised honest users. The advantages of this system compared to prior approaches are it is not bounded by the expected number of attackers, it does not require extra information outside of the learning process and it works with fewer assumptions about clients and their data. However, combating against a single client adversary, improving the model against informed attack are some limitations of this model.

Blanchard et al. [98] first confirmed that federated averaging does not resist Byzantine attacks and then proposed Byzantine-tolerant aggregation rule called *krum* to address the model poisoning attack. Considering f byzantine attackers out of n participants in a communication round, *krum* first calculates the pairwise euclidean distance of n-f-2 updates that are closest

to a model update δ_i and then computes the sum of squared distances between δ_i and its closest n-f-2 updates. Finally, the algorithm updates the global parameter by the model update with the lowest sum. The idea behind this is to choose a vector that is somehow the closest to n f workers and guarantee convergence regardless of f Byzantine attackers.

A work presented in [104] proposed an aggregation rule considering no bound on the number of Byzantine workers but still demonstrated better convergence. The proposed approach computes a score for each worker using a stochastic first-order oracle to determine its trustworthiness. The server ranks each candidate gradient estimator as per the estimated descent of the loss function, and the magnitudes. It then calculates the averaged gradient over the several candidates with the highest score. The server compares the true value of the gradient with the average gradient to identify whether the update is harmful or not.

Sun et al. 2020 [105] study the vulnerability of FL for data poisoning and devise a bi-level optimization framework adaptive to the arbitrary choice of target nodes and source attacking nodes to compute optimal poisoning attacks. Exploiting data collection process, an attacker can directly inject poisoned data to all the target nodes. The authors also considered an indirect way of poisoning data to target nodes by exploiting communication protocol in case direct attack is not possible. This work highlights challenges associated with FL where attackers can exploit the communication protocol to open a backdoor to lunch data poisoning attacks. To adopt FL as probable cybersecurity solution, a cybersecurity mechanism to combat possible threats in FL should be in place. So, we also discuss some research works that present the cybersecurity solutions to the potential threats existed in FL.

To address backdoor attacks in [106], authors presented defense approaches using norm clipping and differential privacy. Norm clipping was considered to combat boosted attacks which are likely to generate updates with large norms. This approach was used to put a bound on the sensitivity of the gradient update by ignoring updates if its norm is above some threshold norm. Furthermore, authors also used differential privacy to supplement norm clipping by adding Gaussian noise to the updates to mitigate the effects of adversaries beyond norm clipping.

In FL, if an attacker does not have a control over the clients, it is still quite possible to lunch man-in-the-middle attacks. He/she can overhear model updates to reveal the privacy of clients and even can forge model updates in transit. To address this attack scenario, techniques like differential privacy [83] homomorphic encryption ([107], [108]) secure function evaluation or multiparty computation [109] and other cryptographic approaches have also been applied on top of FL. Differential privacy is effective to preserve privacy of clients due to added noise on shared model updates and thus mitigates reverse engineering attack while other approaches even mitigate any chance of manipulation of model updates while in transit. However, these approaches adds up computation and communication burden compared to differential privacy approach. Geyer et al. [110] proposed an algorithm for client sided differential privacy preserving federated optimization. It demonstrated that client's participation can be hidden at the cost of minor loss in model performance when sufficient client participates. Article [111] also used differential privacy approach to protect patients' privacy against possible reverse engineering attack.

In [93], Zhu et al. first demonstrated reverse engineering attacks and then presented some defense strategies. Approaches like adding noise on gradients before sharing, gradient compression and sparsification and others were experimented to observe its performance against information leakage. To address reverse engineering attacks by preserving the privacy of end-users, [81] adopted mimic learning approach [112] to work in federated learning scenario. Mimic learning used two kinds of learning models named as a student and a teacher. The student model is trained with public dataset whereas the teacher model is trained with sensitive user data. Then the teacher model is used to label the public dataset which is later used to create a student model and sent to the centralized server for generating a new global model. The approach of transferring knowledge from the teacher model to the student model without revealing any sensitive information was used to protect the student model against reverse engineering attacks.

To strengthen privacy by securing the parameters exchange between client and aggregating server, homomorphic encryption[1] is one of the techniques in which aggregation can be performed directly on the encrypted parameters. This approach allows aggregation without revealing model updates which secures FL from any kind of spoofing or manipulation of model updates. . Taking the computation and communication overhead of this approach into account, Zhang et al. [107] proposed an efficient homomorphic solution called BatchCrypt. To apply this solution, first a new quantization and encoding schemes together with a gradient clipping technique were developed. After this, instead of applying homomorphic encryption on individual gradients, BatchCrypt was used to encrypt an encoded batch of quantized gradients. BatchCrypt demonstrated significant speedup in training and reduction in communication overhead (compared to encrypting each gradient) with negligible loss in accuracy.

Moreover, in recent times, blockchain technology (BC [2] has been extensively applied for many applications due to its decentralized, auditable, secure, and privacy-preserving features. . So, some research works (eg. [82], [83]) have incorporated blockchain in FL setting too. To mitigate the effect of revealing sensitive information while sharing gradient and chance of forging aggregated gradients by a malicious server,

[1]Homomorphic encryption is a special form of encryption that allows specific types of operations to be done directly on encrypted data without requiring a decryption key. The encrypted result when decrypted, confirms the result of operations performed on the plaintexts [113]

[2]Blockchain Technology is a decentralized distributed network that uses public key cryptography, distributed digital ledger and consensus algorithms as core components for creating a secure, transparent, and auditable network to allow people/devices to communicate in a trust-less manner without presence of any intermediaries [114]

a verifiable federated learning (VFL) is proposed in [80]. This approach used Lagrange interpolation and set interpolation points to verify the integrity of the aggregated gradient. The main advantage of VFL is it enables each participant to verify the aggregated parameters. Moreover, the verification overhead also remains constant regardless of the number of participants. Taking operation and security into account, Zhao et al. [74] designed a generic framework of the FL platform by adding a security domain and a cryptographic infrastructure to make trusted connections and interactions among the federated communicating parties. For similar objectives, [115] highlights the most common issues in FL like convergence, data poisoning, scaling, model aggregation with security and privacy perspective and presents potential solutions with simulation results.

A cryptographic approach has been widely adopted as a method of exchanging information and certification to provide security and trust. With the objective of facilitating trusted sharing of cybersecurity certification information following the EU cybersecurity act, work in [61] proposed generic blockchain platform enriched with smart contract acting as a registry for authoritative device information. The smart contract stores information like the manufacturer name, contact information, identity certificate, device type, device id, last firmware version and hash/fingerprint, and a Manufacturer Usage Description (MUD) file describing the typical network interactions and which is published in an off-chain database and others. The proposed blockchain provides a trusted exchange of cybersecurity certification information for any electronic product, service, or process. The authors validated the proposed work by presenting a case study where they used SDN controller to retrieve a MUD file from the device registry smart contract. To secure communication and data transmission between IoT devices and edge node, article [51] proposed Elliptic Curve Cryptography (ECC) based lightweight cryptographic solution embedded in IoT and edge device. The presented approach consisted of three layers consisting of sensors and actuators (layer I), IoT edge (layer II), and cloud (layer II) where most of the computation including key generation takes place in layer II to reduce computation overhead to the IoT-edge. IoT-edge layer extracts the public key sent by the server and updates to IoT devices when required. The proposed approach was simulated by configuring IoT edge and docker and the observed results demonstrated reduced running time of encryption as well as reduced resource demands. VerifyNet [68] utilizes a key sharing strategy and encryption to protect the privacy of the user's local gradients in the workflow. Further, this model used CNN network with MNIST database to test the classification accuracy of the model. The model classifies the correctness of the results returned by the server. Additionally, it also allows users to be offline during the training process.

Cloud service based architecture is the necessary as well as dominant computing services in today's world. The operations and communications associated with the service provider must be secure and trustworthy. To assess the security and reputation of cloud service-based architecture for IoT, Li et al. [72] proposed a novel trust assessment framework. The proposed framework integrated security and reputation-based trust assessment methods to evaluate the trust of cloud services. Customers' feedback rating for the cloud service's trustworthiness or quality of service of cloud service was incorporated in the framework. For the performance evaluation, the assessment framework was built and tested in two parts namely security-based test assessment (SeTA) and reputation-based test assessment (ReTA). SeTA was tested using a synthesized dataset encapsulating security metrics whereas ReTA was tested against WSDream dataset2; a real-world web service dataset and the results demonstrated that the proposed framework efficiently and effectively assesses the trustworthiness of a cloud service while outperforming other trust assessment methods.

A secure data collaboration framework (FDC) consisting of a private data center, public data center, and blockchain technology for IoT environment was presented in [82]. The role of the private data center is to handle data governance, data registration, and data management where that of the public data center is to facilitate multiparty secure computation. Blockchain technology was used to provide auditable multiparty interactions. The framework was implemented in FL setting to address issues like secure and confidential storage, secure sharing and efficient management, traceability and audit of data behaviors, efficient authorization, and others. In another example, PriModChain [83] combined differential privacy enabled FL, blockchain, and smart contract to ensure privacy, security, reliability, safety, and resiliency in the IIoT environment.

To fully protect the privacy of end-users, secure multiparty computation(MPC)[3] approach has also been utilized in FL. [117] used MPC to perform secure FL aggregation where the aggregating server(s) can not access clients' model updates as well as any intermediate global model. To exchange the model update securely, clients use a multi-party encryption scheme to encrypt their updates. Further, to access the global model, the clients decrypt global updates using its secret share of key. After training, clients encrypt their local updates and send it to the server for aggregation.

Despite the several research efforts to make FL secure from attackers controlling end devices and/or acting in the middle, FL can still be vulnerable to centralized server's malfunctioning. Attackers may compromise the aggregating server or server itself may act maliciously. A biased server may manipulate the aggregation process and favor some clients. Considering these possibility, some research (e.g. [118], [119]) have suggested to use the blockchain technology and delegate all the FL operations to end devices so as to remove centralized server. By this approach, end devices acting as the miners of blockchain network collect the model updates, verifies it and finally perform aggregation. This approach addresses several

[3]Secure multiparty computation is a cryptographic protocol that enables distrusting parties to interact and compute a joint function where no individual party can see others' data [116].

security concerns but still fails to address the scenario when the client itself can be malicious. Furthermore, the blockchain approach associates high computation and communication requirements and so, it may not be applicable if the end devices are resource constraint.

Securing FL fully is a huge challenge and it is still an open research topic. Cryptographic approaches are quite useful to exchange model updates securely and preserve privacy however, if the privacy of clients is fully preserved (even to the aggregating server), it is hard to detect malicious model updates and take appropriate measures against colluding attacks. One approach is not sufficient to address all the security concerns associated with FL. Exploring the combination of different approaches discussed above is likely to be a potential solution to address the security issues present in FL.

IV. Resource constraint, Communication latency and Model accuracy

We have already witnessed the success of blockchain in recent times due to its decentralized model of secure computing. In a similar sense, FL research is growing enormously due to its privacy-preserving decentralized learning model. However, the true success of FL depends on its core challenges, and these need to be addressed for its applicability. FL framework not only needs to be secure but also should be efficient and accurate enough. The core challenges that hinder the performance of FL are expensive communication, systems heterogeneity, and statistical heterogeneity. In this section, we discuss several research that have addressed such challenges.

In FL setting, updated model parameters are exchanged regularly between end-devices and a central server and it causes a major bottleneck in the performance of federated networks. To alleviate such communication overhead and reduce latency, approaches like compression e.g. [45], clustering e.g. [46], optimizing global federating learning e.g. [26] time and others have been examined in the literature. The approach to reduce latency might affect the accuracy of the learning model. Several works have also addressed preserving or improving accuracy and in most cases, the accuracy of the proposed solutions has been verified by comparing them with the centralized model.

To alleviate communication overhead in FL, [45] envisioned a compression approach and proposes a new sparse ternary compression (STC) framework. This framework is created by extending the existing compression technique of top-k gradient sparsification. The authors employed a mechanism to enable downstream compression as ternarization and optimal Golomb encoding. The authors conducted experiments on the proposed framework by applying four different learning tasks observed that STC performed well in common FL learning scenarios of high-frequency and low-bandwidth communication. Improving communication efficiency by compressing thus reducing the communicated message size, [78] designed and improved gradient compression algorithm and achieved 8.77% of the original communication time with just 0.03% reduction in the accuracy. This Privacy-Preserving Asynchronous FL Mechanism for Edge, employed collaborative learning of discrete nodes in edge networking with ensuring the privacy of local information. This work also investigated asynchronous FL to better work with diverse characteristics of edge nodes. Preserving accuracy while applying high ratio sparsification in FL, [76] proposes a General Gradient Sparsification (GGS) framework for adaptive optimizers. The framework consists of gradient correction and batch normalization up-to-date with local gradients (BN-LG) to keep convergence to a large extent and to minimize the impact of delayed gradients on the training respectively. Some researchers have addressed communication overhead by tuning the aggregation of the global model. Whereas in [26], Hsieh et al. used the approach of aggregating global model only when the global model's weight differs by some empirically selected threshold. With a similar objective and approach as defined in [26], a control algorithm to find global aggregation frequency was proposed in [27]. The control algorithm devised from theoretical analysis learns the system and data characteristics dynamically in real-time to find the appropriate aggregation frequency that results in enhancing learning accuracy based on the resource available.

Non-IID data distribution in the FL network is likely to affect the quality of the global model. To address such issue, [28] used, a feature fusion approach of aggregating local and global model. The proposed model outperformed baselines FL models and demonstrated better accuracy, initialization for new incoming clients, speeding up the convergence process. Wang et al. [50] propose a control algorithm to work with best trade-off between local update and global parameter aggregation in FL to minimize the loss function under a given resource budget. Considering the effect of statistical heterogeneity, work [29] proposed a novel federated multitask learning (FMTL) framework that forms clusters of clients based on the geometric properties of the FL surface with jointly trainable data distribution. This clustering approach provided better results in FL scenario where clients' local data is distributed and non-IID. The advantages of this approach compared to the existing methods are that it works with the existing FL communication protocol and is also applicable to general non-convex objectives. Furthermore, information about a number of clusters does not require to be known in advance.

Clustering approach has also been sought as a solution to address some FL issues. A work presented in [46] proposes a clustering approach to form a cluster among the densely populated devices. A cluster head is then selected and is responsible for enabling self-organizing FL. Battery life, computation resources, and better connectivity (with other devices) parameters were considered for the selection of cluster head. The cluster head then acts as a central server and carries out aggregation task for FL. The authors also presented a heuristic algorithm to optimize global FL time. For quick convergence of the model, work [52] uses a blockchain-based approach to choose a subset of nodes for updating two types of weights in the global model. One subset updates weight based on its local

learning accuracy and the other on its participation frequency.

In [42], a federated CLONE model is proposed to work on the edges for connected vehicles network. A parameter EdgeServer was used to coordinate distributed participating vehicles. Each vehicle locally trains its learning model with its own private training data. After one epoch, each vehicle pushes the current value of parameters to the parameter EdgeServer and the EdgeServer aggregates all such parameters from distributed vehicles by computing the weighted average value. For the next epoch, each vehicle pulls the updated parameters as the current parameter from the EdgeServer and repeats the process. In case a new vehicle joins the network, it pulls the current aggregated parameters from the parameter EdgeServer to use as its initial parameters for training. Following asynchronous communication without stopping and waiting for other vehicles to complete an epoch reduces the latency.

System heterogeneity is one of the big issues in the federated network which can not be ignored. Ren et al. [20] combined the idea of FL and data offloading to alleviate the constraints and challenges of IoT devices. For intensive computation tasks, IoT devices offload data to the edge nodes so that such devices can conserve energy and provide the required quality of service. Multiple deep reinforcement learning (DRL) agents were deployed on IoT devices to assist in offloading decisions as per the dynamic workload and radio environment of the IoT system. DRL agents were trained in a distributed setting using FL and an experiment was conducted to confirm the effectiveness of edge computing-supported IoT system using data offloading and FL.

Some works incorporated blockchain-based federated model architecture consisting of edge nodes. "FLchain" [71] stores local parameters used for each global aggregation in a block on the channel-specific ledger to enhance security and audit trails. In FLchain, for each new global learning model, a new channel is created. However, the limitations in this model are the blockchain model does not use a reward mechanism for participating nodes, and end devices do not directly participate in BC, in fact, edge devices do all the transactions on behalf of these devices. Moreover, latency of communication, the computing and storage capability of end devices are not taken into account in the proposed model. In [79], authors proposed iFLBC:FL and Blockchain-based ML to bring edge-AI to end devices. To alleviate the scarcity of data, a trained federated shared model is stored in the blockchain that works using the mechanism called Proof of Common Interest (PoCI) to separate relevant and non-relevant data.

V. Machine learning models, algorithms, and technology

In this section, we highlight all the machine learning models, algorithms, and technologies used by surveyed research in Table III. Along with this information, we also present information about the tools and environment under which simulation has been carried out. Our survey is primarily focused on cybersecurity for the IoT environment and importantly using FL. Based on the nature and complexity of the proposed works, authors have adopted a variety of ML models. The only purpose of this section is to give readers information about the trends on kinds of ML models, algorithms, and technologies that have been used by the surveyed works along with the tools and environment under which the proposed works have been evaluated.

For all the proposed works, authors have adopted varieties of machine learning models like a neural network, SVM, linear regression, Q-learning, and so on. FL inherently supports privacy and security (compared to centralized learning) but to strengthen these, some works have also used elliptic-curve cryptography, differential privacy, blockchain and others. The majority of the works have considered CNNs as their machine learning models. Different variations of CNNs like LeNet, AlexNet, GoogLeNet, VGGNet, and others have been used. LSTM (a recurrent neural network) and MLPs (a feed-forward neural network) also have been used by several works. Several works have adopted multiple of the ML models and compared the results to verify their proposed models.

VI. Popular Datasets Adopted to Evaluate Learning Models

Due to the several challenges associated with IoT and cyberphysical systems as outlined inI, these systems have been a primary target of various kinds of cyberattacks in recent times. Because of the huge volume of data flows through the IoT network, data-driven sophisticated anomaly detection systems are necessary for detecting such attacks. A better system needs sufficient high-quality network data to learn the pattern of the compromised network. There have been several works to produce real dataset which can be used to train and test IDS. Moreover, significant efforts also have been devoted to creating datasets to evaluate the performance of FL models. So, in this section, we classify research works based on the dataset it uses for their proposed work in table IV. This classification gives an idea about the most common datasets that have been utilized by several works considered in this paper. We also discuss what these datasets are and what they contain so that it might be useful for researchers to choose the dataset based on their needs.

KDDCup99 [132] and NSL-KDD [121] are popular intrusion detection datasets, both containing five major intrusion categories as listed below:

- Normal: No intrusion in the network.
- Denial of service (DoS): Making network resource unavailable by overwhelming it with information and requests
- Remote to user (R2L): An attack involving unauthorized access to a user machine from a remote machine
- User to root attacks (U2R) : Intruder gain access to a network as a legitimate user
- Probe: Scanning the network to identify weaknesses

KDDCup99 is an intrusion dataset created in 1999 with the objective of improving the capability of IDSs. The training set of KDDCup99 contains 3,925,650 attack records and in which

TABLE III
MACHINE LEARNING MODELS, ALGORITHMS AND TECHNIQUES USED IN STATE OF HE ART RESEARCH WORKS

Model	FL	ML Models, Algorithms, Technology	Tools and Environment
[49]	✓	SVM	CORE/EMANE Network emulator, TensorFlow
FoolsGold [30]	✓	Softmax classifier, SqueezeNet1.1,	FL prototype using python, VGGNet11
[50]	✓	Squared-SVM, linear regression, K-means, DCNN	Raspberry Pi, Laptops
[55]	✓	SVM, LSTM	virustotal api
PAFLM [78]	✓	three-layer MLP, threshold gradient compression	GPU server,PCs
[31]	✓	IDS	Simulated using Raspberry Pi devices
DeepFed [32]	✓	CNN-GRU,IDS, Paillier cryptosystem	CPU,GPU,Keras API, Flask
FNTAE [56]	✓	KNN	Simulated on workstations
DÏoT [65]	✓	DNN,GRU,IDS	Simulated using IoTs and Gateways
VerifyNet [68]	✓	CNN, Elliptic-Curve	PCs
VFL [80]	✓	Lagrange interpolation, MLP, CNN	Simulated using PCs and Alibaba cloud
[81]	✓	MLPs	Tensorflow, Keras
FDC [82]	✓	DNN, blockchain	Libra, Tensorflow
PriModChain [83]	✓	DNN, Blockchain,Smart contract, Differential privacy	Python, Ethereum, Ganache, Kovan, Scyther
FED-IIoT [85]	✓	GAN	Tensorflow, Keras
[3]	✓	CNN	Simulated at LAN-security Monitoring Project
“Gaia [26]	✓	GoogLeNet-CNN,	Amazon-EC2, Emulation-EC2
[27]	✓	SVM, CNN, linear regression, K-means	Simulated using Raspberry Pi and laptops
[58] [115]	✓	CNN	✗
[75]	✓	Q-learning	Ns-3 for mobility
[77]	✓	SAE	LEAF [120]
[28]	✓	CNN	✓
ASTW_FedAVG [47]	✓	CNN,LSTM	Simulated with designed framework
FLchain [71]	✓	Linear regression	✗
[84]	✓	DNN	Simulated with designed framework
STC [45]	✓	sparse ternary compression, LSTM, LR, VGG11	Simulated with designed framework
CLONE [42]	✓	LSTM	Intel FogNode and Jetson TX2
[20]	✓	DRL	IoTs
iFLBC [79]	✓	ML, Blockchain	Simulated with designed framework
[52]	✓	MLP	Simulated with designed framework
DRAFT [54]	✗	-	Fed4FIRE+federated testbeds
[74]	✓	✗	Theoretical concept only
[46]	✓	clustering algorithm	✓
CFL [29]	✓	DCNN, DRNN, clustering	Simulated with designed framework
[76]	✓	CNNs-LeNet-5, DenseNet-121, CifarNet, AlexNet	Simulated with designed framework

only 262,178 records are distinct whereas the test set includes 250,436 attack records and in which only 29,378 records are distinct. In the case of normal traffic data, the training set contains a total of 972,781 records with 812,814 distinct records, and similarly, in the test set, 47,911 records are distinct among 60,591 total records. NSL-KDD is the subset of KDDCup99 created in 2009 to rectify the inefficiencies associated with KDDCup99. The main issue with the KDDCup99 is that it contains significant redundant records which tend the learning model to be biased toward the more frequent records [121].

Kyoto 2006+ [133] is another NIDS evaluation dataset that was produced by processing the data collected from 348 honeypots deployed in 5 different networks (inside and outside) of Kyoto University. Real as well as virtual machines including two black hole sensors with 318 unused IP addresses were implemented as honeypots to capture the real network traffic data over the 3 years of span(2006-2009). During this time span 50,033,015 normal sessions, 42,617,536 known attack sessions, and 425,719 unknown attack sessions were gathered and which were processed further to extract 24 features including 14 derived from the KDDCup99 dataset.

VirusTotal API [134] is a cyberthreats scanning service allowing users to analyze files or URL address online. It consists of a large set of analyzers including antivirus application engines and website scanners from more than 60 security vendors. With the VirtusTotal service, users can get a thorough analysis report for submitted files or URLs and if needed, previous analysis reports can also be obtained. The VirusTotal API provides scanning results as a JSON object and with that, an evaluation dataset can be developed as required.

Aegean Wi-Fi Intrusion Dataset (AWID) [122] is another intrusion dataset that comprises real incidents of both normal and anomalous activities that occurred in the 802.11 Wi-Fi networks. Each record in the dataset contains 155 attributes with a class attribute for specifying whether the record represents normal or attack traffic. As per the class distribution,

This article has been accepted for publication in IEEE Internet of Things Journal. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2022.3150363

TABLE IV
LIST OF DATASET USED BY VARIOUS RESEARCH WORKS IN THE FIELD OF CYBERSECURITY

Dataset	Dataset used in References	Federated Learning
NSL-KDD [121]	[31], [81]	✓
AWID [122]	[77]	✓
MNIST [123]	[27], [49], [52], [68], [80], [115]	✓
MNIST, Cifar-10 [124]	[78] [29] [28]	✓
MNIST,HAR [125]	[47]	✓
ImageNet	[26]	✓
CIFAR,KWS [126],MNIST	[45]	✓
MNIST, VGGFace2 [127], KDDCup , Amazon reviews [128]	[30]	✓
MNIST, MNIST-F, CIFAR-10	[50]	✓
MNIST, CIFAR-10,ImageNet [129]	[76]	✓
KDD99 [128]	[56]	✓
KDD99 , NSL-KDD	[62]	✗
Mirai [130]	[65]	✓
KDDCup 99 ,NSL-KDD, UNSW-NB15 [86], Kyoto, WSN-DS, CICIDS 2017	[63]	✗
Drebin, Genome, Contagio	[85]	✓
Wearable sensor data collected at kindergarten	[82]	✓
Fed4FIRE+federated testbeds [131]	[54]	✗
KDD, NSLKDD, UNSW-NB15, N-BaIoT	[84]	✓
virustotal api	[55]	✓

AWID has been divided into two major types as a high-level labeled dataset (AWID-CLS) and a finer-grained labeled dataset (AWID-ATK). AWID-CLS is created from a large set of packets whereas the other is from the smaller subset. These two sets of the dataset are formed by capturing packets at different times, in different environment, and with different types of equipment and contains their own set of training and test set. Each record in AWID is classified as either normal or a particular intrusion type. The intrusion types in AWID-CLS are categorized into 4 major classes named as Flooding, Impersonation, Injection, and Normal whereas AWID-ATK specifies more detailed class labeling. The training set of AWID-ATK comprises 10 classes whereas a test set contains additional 7 classes. The large dataset contains 162,375,247 records for training and 48,524,866 records for testing while the reduced dataset contains 1,795,575 and 575,643 records for training and testing respectively [122].

UNSW-NB15 [86] is another intrusion dataset to evaluate network intrusion detection systems (NIDSs). The motive behind creating this dataset is to mitigate the deficiencies of past intrusion dataset and help to identify new and emerging cyberattacks and including low footprint attacks. UNSW-NB15 dataset was created by Australian Centre for Cyber Security (ACCS) that includes real modern as well as synthesized network traffic. A synthesized dataset containing both normal and abnormal traffic was created in lab setup using IXIA PerfectStorm tool [135]. This tool contains all the updated publicly known attack information and was used to simulate nine families of attacks named as normal, fuzzers, analysis, backdoors, DoS, exploits, generic, reconnaissance, shellcode, and worms Further, other sets of tools and algorithms were also utilized to generate 49 features to covers characteristics of network packets.

WSN-DS [136] is an intrusion dataset created for wireless sensor network (WSN) to train and evaluate IDSs to effectively identify four classes of DoS attacks namely blackhole, grayhole, flooding, and scheduling attacks. To collect data for creating WSN-DS, a WSN environment was simulated using Network Simulator 2 (NS-2) where LEACH [137] protocol was applied as a routing protocol. The collected dataset was then processed and 23 features were produced. The usefulness of the dataset was evaluated by training and testing an Artificial Neural Network (ANN).

In another attempt to develop an intrusion dataset having the latest threats information and features, the Canadian Institute of Cybersecurity created CICIDS 2017 [60] by collecting five days' network data containing normal and attack traffic in the network environment of the Canadian Institute of Cybersecurity over eight different files. All the files were processed and merged and finally, a single dataset fulfilling all the criteria of true intrusion dataset was produced. The resultant dataset has 2830540 records and each record has 83 features including a class label that represents either normal traffic or one of the 14 attack classes.

Mirai actually is not a dataset rather, is a worm-like malware that was launched in 2016 [130]. The malware infected distributed IoT devices and transformed them into a botnet which finally caused one of the most popular DDoS attacks in history. The source of the Mirai attack is publicly available and it is popular among the research community. The source code is launched in an IoT network environment and network traffic is collected and analyzed to create an intrusion dataset and moreover, it is also used to evaluate the performance of the developed IDS model.

Fed4FIRE+ [131], a successor of Fed4FIRE, is a project under the European Union's Programme Horizon 2020 started in 2017 with the aim of providing open, accessible, and reliable facilities for supporting experimentally driven research. It provides the largest federation worldwide of Next Generation Internet (NGI) testbeds. It aims to support re-

search and innovation communities and initiatives in Europe, including the 5G PPP projects and initiatives. Fed4FIRE+ enables various innovative experiments through the federation of the infrastructures. Moreover, it offers federated hardware and software testbed resources by which an emulation of network environment can be easily created and cyberattacks experimentation can be conducted efficiently and effectively.

FL research substantially utilizes several machine learning and deep learning models and the availability of accessible benchmark datasets allows better training and testing of these models. There have been ample works to create such standard realistic datasets and those have been significantly used in literature. MNIST (Modified National Institute of Standards and Technology) dataset [123] is one of the most popular and frequently used of such datasets. It is a simple and most beginner-friendly labeled dataset containing 70,000 images of handwritten digits from 0 to 9. There are different variations of MNIST named as MNIST-F and MNIST-O. MNIST-F which is fashion MNIST contains a more sophisticated alternative image dataset related to 10 categories of fashion items. MNIST-F is widely adopted for CNN because of its simplicity to use.

CIFAR-10 (Canadian Institute For Advanced Research)) [138] is another image dataset consisting of 50,000 training and 10,000 test images categorized over 10 classes. MNIST-F contains grayscale images whereas CIFAR-10 is a dataset containing color images and is one of the widely used computer-vision datasets for object recognition.

The rapid rise in the availability of multimedia data and enhancement of computing capabilities has assisted on the advancement of building sophisticated and robust machine learning models. Simple datasets on those sophisticated ML techniques have been no longer useful to identify the true potential of these algorithms. A need for a complex dataset is inherent to achieve better results and such necessity led to create ImageNet [129] dataset. It is a large-scale dataset with high diversity and accuracy compared to most of the existing benchmarked image datasets and is useful mostly for image classification, object localization, and object detection. The dataset is a repository of 80,000 synsets of WordNet with an average of 500-1000 clean and full resolution images. The dataset has 12 subtrees 3.2 million cleanly annotated images spread over 5247 categories.

VGGFace2 [127] is a large-scale face dataset consisting of 3.31 million images of 9131 subjects ranging from a wide range of ethnicities, professions, poses, ages, illuminations. Google image search was used to download images for all the subjects keeping approximate gender balance. The dataset contains images with human-verified bounding boxes around faces and five fiducial keypoints predicted by cascaded CNN. The dataset has been partitioned into a training set consisting of 8631 classes and a test set of 500 classes.

HAR (Human activity recognition) [125] dataset is a collection of records gathered from activities of daily living (ADL) of 30 subjects where subjects were equipped with a waist-mounted smartphone with embedded inertial sensors. This dataset is also publicly available and has been widely used by researchers for activity recognition tasks.

KWS (keyword spotting) is an activity of identifying keywords from text images, voice commands and others, however, in this paper we discuss audio dataset [126] used in the research presented in [45]. The dataset contains a collection of 105,829 utterances of 35 words of 2168 speakers. Each utterance is stored in WAVE format file with a length of a maximum of one second. The dataset is useful widely used for the training and evaluation of speech recognition models.

Amazon reviews [128] dataset is produced from a corpus of text in the form of the product reviews by customers on the Amazon commerce website for authorship identification. The recordset contains 1500 instances with 10,000 attributes and 50 classes. Each record contains attributes related to authors' linguistic style like usage of the digit, punctuation, words and sentences' length, usage frequency of words, and so on.

VII. Open challenges and future research directions

Data is a crucial asset for an individual and company that should be protected to ensure the CIA (confidentiality, integrity, and availability) triad. Legislations like Consumer Data Protection Act and the Data Care Act in the USA, General Data Protection Regulation (GDPR) in Europe have been already rolled out to strengthen data protection. However, due to the rapidly growing flood of data, ML has been inevitable to analyze and learn from the data. However, the traditional learning model (centralized) poses a lot of concerns due to the insecure digital highway, limited bandwidth, and sole control of the service provider. In this regard, FL offers an innovative framework to facilitate learning by keeping data locally and training locally. However, it is still in the early stage to be fully applicable particularly for the IoTs environment. In recent times, FL has gained significant attention in the research community. Many works have already proposed their models making use of different ML algorithms, frameworks, and technologies. However, in our survey, we found most of the proposed models use neural networks. NN is mostly preferred in FL setting however, it increases the complexity which might increase the overhead in real heterogeneous IoT environments. Moreover, most of the proposed models are simulated in an environment consisting of few devices and that are tested against only a few datasets. To develop an efficient and robust FL model, research works need to consider different permutations and combinations of ML algorithms, datasets, and working dynamics and measure the true efficacy of the developed system.

Considering the limited resources and communication bandwidth in the IoT network, a significant number of research works have proposed a FL scenario where the edge server aggregates the updates from end devices and passes them on to the central server. Such an approach might not work in general as all IoT networks may not have such an ideal configuration. Additionally, the baseline algorithm, federated averaging (FedAvg) has been mostly applied to aggregate and weigh the updated model. Due to the system and statistical heterogeneous

characteristics of IoTs environment, the convergence in real federated networks may not occur as expected. So, it will be valuable to seek other methods that address such issues and result in quick convergence.

Differential privacy e.g [23], homomorphic encryption e.g. [25] , secure function evaluation or multiparty computation e.g. [24] have been utilized in FL for privacy-preserving learning. FL using these approaches have been implemented and experimented in small-scale distributed network only. So, it may bring novel challenges in the large-scale network scenarios due to the additional communication and computation burdens.

In literature, gradient compression schemes [e.g. [76], [45]] have been popularly applied to compress the communicated messages to thus reducing latency. Although this reduces the size of data to be transmitted, it may result in data loss and affect the accuracy of the learning model.

In surveyed works, the ML learning parameters have been aggregated in a single centralized server. This approach induces the risk of a single point of failure due to a cyberattack or any other reason. Moreover, In this setting, communication efficiency is also likely to be affected by the geographical location of the centralized server. A new approach to design multi-tier distributed aggregating servers can make FL communication efficient and robust.

Several methods have been proposed to address expensive communication in FL, however, those approaches have been tested only in the small scale federated networks. Such approaches may perform inefficiently in large-scale federated networks consists of millions of devices with system heterogeneity and statistical heterogeneity. In a large-scale network setting exacerbated by devices sampling and drop out due to network connectivity and limited resources, current approaches are limited to measure the level of system heterogeneity as well as statistical heterogeneity. This deficiency might directly hinder the accuracy of the learning model. large-scale FL have been highlighted in many articles. These issues have been addressed mostly under the assumptions of i.i.d., non-modified and equal data distribution. Identifying and mitigating attacks on true FL stetting without degrading performance and accuracy is still an open area of research.

VIII. Conclusion

In this survey, we first highlighted the risks and threats associated with IoT systems. Motivated by the role of ML to learn from the flood of data and keep the IoT network safe and secure, we talked about different models of learning and pinpointed the merits and demerits of each model. We then extended our study to the application of FL, a new and innovative learning model; for the security of IoT networks. Several recent works addressing the security aspect of IoT environments were discussed. We also discussed several research efforts carried out to mitigate attacks in the FL paradigm. Despite the inherent data protection framework of FL, it bears several challenges to be addressed for its successful adoption. So, we discussed several existing research addressing such performance issues. To assist readers for a research direction with overall information, we presented most of the surveyed works along with the issues addressed and all the ML algorithms, frameworks, technologies, datasets used by the proposed works. Finally, some open challenges in FL research were presented for future research directions.

Acknowledgment

This research was funded in part the DoD Center of Excellence in AI and Machine Learning (CoE-AIML) at Howard University under Contract Number W911NF-20-2-0277 with the U.S. Army Research Laboratory and in part by the U.S. National Science Foundation (NSF) under the grant CNS/SaTC 2039583 and 1828811 as well as in part by NNSA MSIPP Grant.

Any opinion, finding, and conclusions or recommendations expressed in this document are those of the authors and should not be interpreted as necessarily representing the official policies, either expressed or implied, of the funding agencies.

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This article has been accepted for publication in IEEE Internet of Things Journal. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2022.3150363

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