Security and Machine Learning Adoption in IoT: A Preliminary Study of IoT Developer Discussions

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Abstract—Internet of Things (IoT) is defined as the connection between places and physical objects (i.e., things) over the Internet/network via smart computing devices. IoT is a rapidly emerging paradigm that now encompasses almost every aspect of our modern life. As such, it is crucial to ensure IoT devices follow strict security requirements. At the same time, the prevalence of IoT devices offers developers a chance to design and develop Machine Learning (ML)-based intelligent software systems using their IoT devices. However, given the diversity of IoT devices, IoT developers may find it challenging to introduce appropriate security and ML techniques into their devices. Traditionally, we learn about the IoT ecosystem/problems by conducting surveys of IoT developers/practitioners. Another way to learn is by analyzing IoT developer discussions in popular online developer forums like Stack Overflow (SO). However, we are aware of no such studies that focused on IoT developers’ security and ML-related discussions in SO. This paper offers the results of the preliminary study of IoT developer discussions in SO. First, we collect around 53K IoT posts (questions + accepted answers) from SO. Second, we tokenize each post into sentences. Third, we automatically identify sentences containing security and ML-related discussions. We find around 12% of sentences contain security discussions, while around 0.12% sentences contain ML-related discussions. There is no overlap between security and ML-related discussions, i.e., IoT developers discussing security requirements did not discuss ML requirements and vice versa. We find that IoT developers discussing security issues frequently inquired about how the shared data can be stored, shared, and transferred securely across IoT devices and users. We also find that IoT developers are interested to adopt deep neural network-based ML models into their IoT devices, but they find it challenging to accommodate those into their resource-constrained IoT devices. Our findings offer implications for IoT vendors and researchers to develop and design novel techniques for improved security and ML adoption into IoT devices.

Index Terms—IoT, Security, Machine Learning, Developer Discussions.

I. INTRODUCTION

Internet of Things (IoT) is a rapidly emerging paradigm that is defined as the connection between places and physical objects (i.e., things) over the Internet/network via smart computing devices [3], [20]. This technological revolution now encompasses almost every aspect of our modern life and is not showing any signs of slowing down to evolve into new domains (e.g., smart cars, smart home, etc.) [2], [31]. Indeed, between 2013 and 2020, the number of smart connected devices has increased by more than 1000%, from 5 billion to more than 50 billion [12]. As such, interests in IoT technologies is pervasive among developers to develop smart connected software ecosystems [45].

The access to diverse and large sensor data generated by the IoT devices have created opportunities to adopt Machine Learning (ML) into IoT-based solutions [27]. At the same time, the pervasiveness of the IoT devices in our everyday life has necessitated the developers to adopt security techniques and tools into their IoT devices. [13], [15], [16], [34], [42]. Security concerns for IoT devices can be multifaceted like the implementation/adopter of security protocols (e.g., zigbee chain reaction [32]) and roles (e.g., authentication [19]), the communication over the network like (e.g., cross-device inference [13]), as well as the underlying hardware [22]. Indeed, adoption of security and ML techniques into low-powered but omnipresent IoT devices requires efforts of unprecedented nature unlike anything we have seen before [34]. As such, it is important to understand the challenges IoT developers face during their adoption of security and ML practices, so that we can design effective techniques to address the challenges.

With interests in IoT growing, we observe discussions of IoT developers in online forums like Stack Overflow (SO). To date, there are around 120 million posts and 12 million registered users on Stack Overflow [30]. Previously, several research has been conducted to analyze SO posts, e.g., to analyze discussions on big data [4], concurrency [1], programming issues [7], blockchain development [41], microservices [6], and security [46]. However, we are aware of no research that analyzed IoT security and ML-related discussions on SO, although such insight can complement existing IoT literature that so far has mainly used surveys [2], [3], [20].

In this paper, we present a preliminary empirical study that we conducted to understand security and ML adoption in IoT devices based on the discussions of IoT developers in SO. First, we collect 53K IoT posts from SO based on 78 IoT tags (Section II). Second, we tokenize the posts into sentences, which resulted in around 672K sentences. Third, we automatically label each sentence with two labels: 1) ‘HasSecurity’ is 1 if the sentence contains security discussions and 0 otherwise, and 2) ‘HasML’ is 1 if the sentence contains ML-related discussions and 0 otherwise. We use the labels to answer two research questions (Section III).

RQ1. How do developers discuss security issues while using IoT techniques and tools? This question focuses on understanding security issues from IoT developer discussions in SO. We find that around 12% of all sentences contain discussions about security, i.e., IoT developers frequently are concerned about security requirements and problems in their IoT devices. Their security concerns are multifaceted like involving the secure access/transmission of data across IoT devices and users, and the diverse errors and incompatibilities
they experience while enforcing security protocols across the diverse IoT devices.

**RQ2. How do IoT developers discuss machine learning issues and is there any overlap with security issues?** This question aims to understand how IoT developers are adopting ML-specific techniques/services into their IoT devices. We observed 0.12% of sentences containing ML-related discussions, i.e., the ML-discussions are less prevalent than security discussions. There is no overlap between the security and ML discussions, i.e., IoT developers in SO working on security may not be working on ML adoption at the same time. We find that IoT developers are interested to adopt deep neural network-based ML models into their IoT devices, but they find it challenging to accommodate those into their resource-constrained IoT devices.

Our findings offer implications for IoT vendors and researchers to develop and design novel techniques for improved security and ML adoption into IoT devices.

**Replication Package:** [https://github.com/disa-lab/SERP4IoT2021](https://github.com/disa-lab/SERP4IoT2021)

## II. Data Collection

We follow three steps to collect SO posts related to IoT discussions: (1) Download SO dataset, (2) Identify IoT tagset in the dataset, and (3) Download IoT posts from the dataset based on the IoT tagset. We describe the steps below.

**Step 1. Download SO Dataset.** We download the SO data dump [37] of September 2019 and use the Posts table in the dump for our analysis. A post can be a question or an answer in the Posts table. An answer to a question is flagged as accepted, if the user who has asked the question marked the answer as accepted. A question can have between 1 and 5 tags. The SO dataset includes all posts for 11 years between 2008 and September 2019. In total, it has 46,767,375 questions and answers. Out of those around 40% are questions and 60% are answers. Out of the answers, around 34% are accepted.

**Step 2. Develop IoT Tag Set.** We use tags in SO to identify IoT posts based on an algorithm originally proposed by Yang et al. [47]. The approach starts with a list of initial tags as seed data. Then the approach uses two metrics to automatically expand the list of tags. We discuss each step below.

First, we identify a list of initial IoT tags in SO that frequently co-occurred with the ‘iot’ tag. This resulted in a list of 20 relevant tags based on SO search engine like ‘raspberry-pi’, ‘arduino’, ‘windows-10-iot-core’, ‘python’, etc. From this list, we removed potentially irrelevant tags like ‘python’. We found that the rest of the tags can be clustered into three broad types: 1) iot or any tag with ‘iot’ keyword, e.g., ‘azure-iot-hub’, 2) arduino, and 3) raspberry-pi. Besides the iot tags, arduino and raspberry-pi are the two most popular open source platforms to develop IoT based applications (with dedicated SDKs). Both platforms have undergone rapid evolution through multiple versions, such as raspberry-pi, raspberry-pi2, etc. We note the list of initial tags as \(\mathcal{T}_{init}\).

Second, we check the entire list of SO tags that could be relevant to the three tags in \(\mathcal{T}_{init}\). Suppose, the entire SO data dump is denoted as \(\mathcal{D}\) and the list of all tags in the SO data dump is \(\mathcal{A}\). We extract a list of all questions \(\mathcal{P}\) from our dataset that are labeled as at least one of those tags in \(\mathcal{T}_{init}\). Not all the tags in \(\mathcal{A}\) may correspond to IoT (e.g., ‘python’). Therefore, following previous research [3, 47] we systematically filter out irrelevant tags and finalize a list of all potential IoT tags \(\mathcal{T}\) from \(\mathcal{A}\) as follows. For each tag \(t\) in \(\mathcal{A}\), we compute its significance and relevance with regards to \(\mathcal{P}\) and \(\mathcal{D}\).

\[
\text{Significance } \mu(t) = \frac{\# \text{of Questions with tag } t \text{ in } \mathcal{P}}{\# \text{of Questions with tag } t \text{ in } \mathcal{D}} \quad (1)
\]

\[
\text{Relevance } \nu(t) = \frac{\# \text{of Questions with tag } t \text{ in } \mathcal{P}}{\# \text{of Questions in } \mathcal{P}} \quad (2)
\]

A tag \(t\) is significantly relevant to IoT discussions if \(\mu(t)\) and \(\nu(t)\) are higher than a specific threshold. Our 49 experiments with a broad range of threshold values of \(\mu = \{0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.35\}\) and \(\nu = \{0.001, 0.005, 0.01, 0.015, 0.02, 0.025, 0.03\}\) show that \(\mu = 0.3\) and \(\nu = 0.001\) allow for a significantly relevant set of 78 IoT tags. The threshold values are consistent with previous work [1, 5, 47]. The 78 IoT tags cover a wide range technologies and services supporting the emerging IoT ecosystems. Our replication package lists 78 IoT tags.

**Step 3. Download IoT Posts.** Our final dataset consists of all posts tagged as at least one of the candidate 78 tags. We found a total of 81,651 posts (questions and answers) in our SO dump, out of which around 48% are questions (i.e., 39,305) and 52% (42,346) are answers. Following previous research [5, 7, 33], we only consider the questions and accepted answers to the questions. Our final dataset consists 53,173 posts (39,305 questions, 13,868 accepted answers).

## III. Empirical Study

We answer two research questions using the 53K IoT posts:

**RQ1. How do developers discuss security issues while using IoT techniques and tools?**

**RQ2. How do IoT developers discuss machine learning issues and is there any overlap with security issues?**

The first question (RQ1) focuses on understanding security issues in IoT as developers discuss those in SO. The second question (RQ2) aims to understand how IoT developers are using/adopting ML into IoT devices, which are often resource constrained like low computing storage/processing power, etc. While the adoption of security and ML into IoT devices is gaining attention, it is not known whether both requirements are considered simultaneously and whether IoT developers discuss those two requirements together in SO.

### A. IoT Security Issues in Developer Discussions (RQ1)

#### 1) Approach: Not all discussions in an SO post may be related to security. We therefore detect sentences in SO that contain security discussions as follows. First, we produce a benchmark dataset of 5,297 sentences from SO, each labeled as 1 (contains security discussion) or 0 (otherwise). Out of the 5,297 sentences, 4,297 sentences are taken from a benchmark
of API reviews previously developed by Uddin and Khomh to develop the Opiner tool [40]. Opiner is an online portal to mine and summarize reviews from SO about diverse API aspects (e.g., performance, security, etc.). Each sentence in the Opiner benchmark is labeled as one or more API aspect. The Opiner dataset does not include any sentence related to IoT discussions. We, therefore, randomly sampled 1,000 sentences from our IoT dataset of 53K posts. We do this by tokenizing each post into sentences and then sampling 1,000 sentences from the sentences. Second, we trained a suite of shallow and deep learning models on the benchmark of 5,297 sentences. Third, we evaluate the performance of the models to correct detect security-related sentences in another validation dataset of 984 sentences. The validation dataset is sampled from our 53K IoT posts. The validation and training (i.e., benchmark) datasets are mutually exclusive. The best performing classifier was RoBERTa, an advanced pre-trained language-based models, which shows an F1-score of 0.91 (Precision 0.97, Recall 0.87). The high accuracy of the model denotes that the model can be reliably used to automatically collect IoT developers’ security discussions. Fourth, we applied the trained RoBERTa model on our entire 53K IoT posts to automatically label as sentence as 1 (i.e., contains security discussion) or 0. The details of the benchmark creation process and the models can be found in our technical report [17]. We have also shared in our replication package the code of RoBERTa and the benchmark that is used to train the model.

2) Results: We found total 672,678 sentences in our 53K IoT posts, out of which 30,192 sentences are labeled as 1 (i.e., they contain security discussions) by our RoBERTa model. In Table I we show the distribution of the security-related sentences in the 53K posts. The 30,192 sentences correspond to 4.49% of our entire dataset. The security-related sentences are found in 5,354 questions (#Questions in Table I), which correspond to 13.62% of all the total 39,305 IoT questions in the dataset. Out of the 13,686 accepted answers in the IoT dataset, 12.5% answers contain discussions about security (#Answers column). The numbers denote that IoT security-related discussions are prevalent and frequent in SO.

Table I lists the most frequent keywords in the IoT security discussions. The font size of a word is proportionate to its frequency of occurrences relative to all keywords in the in the 30K security-related sentences. We remove stopwords before we generate the wordcloud. The occurrences of the keywords are not mutually exclusive all the time, i.e., multiple keywords could appear together in one sentence. We discuss the keywords with examples below.

(1) data (2890)-related security issues are discussed in various contexts like access control to a data source, encryption, secure transformation of data during transmission, etc. For example, developer here asks questions about the feasibility of creating random number from microcontroller to apply to cryptography: “the question is about the feasibility of using microcontroller-gathered data to generate random numbers that could be applied soundly to cryptography— an alternative to relying on a device’s entropy.” Q10864664

(2) device (2607) keyword appeared in discussions related to the secure connection and/or communication between multiple IoT devices or between a non-IoT and IoT device. For example, this developer wants to create a remote-controlled door lock “I’m now using the Arduino + WiFiShield to create a door locker which could control the door lock remotely by a portable device with its browser.” Q19891733

(3) user (2450) keyword is found users to an IoT device need to access/user it securely, e.g., “Essentially I want users of the app to be able to login using an RFID card as opposed to inputting their user name and pin, but I still have a lot of work to do to get this done.” Q12023328

(4) security (2266) keyword was used when developers were concerned about security risks of their IoT devices/solutions in general, e.g., “I would like to have some sort of security, in that I don’t want anyone else to be able to contact my RPi and operate it.” Q12375979

(5) code (2184)-related security discussions concerned about the implementation of security practices during coding. Developers worried about writing plain-text passwords in source code: “This password is written in the code and I would like to hide the password from malicious readers who have access to the .o files and .hex files.” Q10326698 Developers also struggled with migrating legacy code into IoT devices: “but I still don’t know how to modify the old code with these OAuth

| Table I: Distribution of sentences & posts with security discussions |
|---------------------------------------------------------------|
| #Sentences | %Total | #Questions | %Total | #Answers | %Total |
|-------------|--------|------------|--------|----------|--------|
| 30,192      | 4.49%  | 5,354      | 13.62% | 1,734    | 12.50% |

1Word clouds are created using the Python WordCloud API
2We use stopwords from Python NLTK [29]
3Q and A denote a question or an answer in SO with ID i
codes to get it working again.”

(6) **file (2179)** related concerns are discussed to secure the access to a file in an IoT device, e.g., Q14678552 “The called python file makes use of the GPIO so sudo is required, right?” Developers also discussed errors that occurred during secure file access, e.g., “When I try to link my sql file (lahman2012.sql) to the database I get an error even though I use the password above (password)”.

(7) **server (2105)** related concerns that occurred around the the setup of client/server architecture involving multiple IoT devices. For example, the developer wants to open a client/server socket over an Arduino serial connection: “I would like to open a client or server socket on the processing program so i can talk to it via WiFi and control my Arduino over serial connection.” Q10907872 Developers also discussed about the potential threats of exposing private keys across similar IoT devices in a network, because if the server is compromised all the IoT devices will be compromised: “But I am wondering if it is a threat to issue the same private key to many devices, that if one device’s key is stolen, the whole service on the server side is compromised.”

(8) **access (2088)**-related issues can arise due to the secure use of a service/resource. Incompatibilities can arise when the authentication is designed for non-IoT environment (e.g., Windows): “We have a web page that we want to access from a raspberry pi, however the web page in question is protected with windows authentication.” Q1565212 Access problems also occurred when developers attempted to executed shell/python script over an IoT device (e.g., RPI) through the secure connection (e.g., SSH): “I have a Raspberry pi that I have been accessing through SSH, but now I need to run a python program on it that has a GUI.” Q16329069

(9) **wifi (1929)** issues are dominant when developers attempted secure protocols over wifi connection or to dynamically configure the wifi network configuration in an IoT device: “My problem is that i want to create a script on my rpi to automatically change wifi networks and change eth0 between static and dhcp.” Q12646278 Developers also found IoT software libraries work well in simulation but not in an wifi-enabled secure environment: “The library seems to work but I can’t figure out the way to connect to a wifi using a password.”

(10) **password (1828)** changes can be problematic in IoT devices: “I am using Raspberry Pi (Debian 3.1.9+ armv6l linux) and javaSE 7 and I am trying to change my truststore password by keytool but keytool command is not working So can you please tell me how can i change my truststore password in this environment.” Q13579503 Setting up access points and the configuration of SSID and passwords in IoT devices are also found as challenging: “I’m trying to setup an Arduino to setup an access point to configure SSID and password for connecting to a Wi-Fi network.”

(11) **key (1824)** store and change are required to securely load and use apps in IoT devices. This can be challenging like when an IoT device (e.g., smart home system) is configured to run third-party software: “I changed out appkey.c for my appkey as given by spotify but when I run the spshell example and try to login, I get an error”

(12) **authentication (1656)** parameters and values can be challenging to pass across IoT devices: “Is there any way to pass this authentication across from the Raspberry pi?” Challenges related to secure messaging passing are discussed. For example, this developer experienced authentication error and automatic disconnection while attempting to establish secure messaging using MQTT: “When I try to connect to nodeMCU wifi using my smart phone (just to test the connection, I have no intention of using this system for heavy Internet load, only MQTT messages) I get a message “authentication error occurred” even though I have typed the password correctly, or (in rarer cases)it connects but disconnects immediately.”

(13) **private (1474)** dev server setup can be challenging in IoT devices due to space limitations: “Now i was curious how much space I have used until now after installing all the packages I needed for a private dev server.” Developers worried about the access private vs public libraries across IoT devices due to privacy issues: “The twist is that I don’t want to put this a std Arduino library location, I want it to be a “private” library that’s visible to and used by only these two sketches.”

(14) **ssh (1403)**-based communication can be problematic in IoT devices when IoT ports are not properly configured to support that. For example, this developer struggled with the setup of ports to access nginx web server from a raspberry pi device: “I have set my router to port all ports from 1 - 9999 just to see if it works but I can’t ssh onto my pi using the public ip address only my local one works, and I am also unable to access my nginx web server on my pi.”

(15) **connect (1400)** issues are common when IoT developers attempted to connect multiple devices and servers to an IoT devices. For example, this developer struggled to securely connect an rpi device to a MySQL database through a pre-configured PHP script: “I have a little Raspberry Pi server set up, using Nginx and Raspbian, and I downloaded a PHP script to serve as a login handler, except that I can’t seem to connect to my MySQL database.”

**RQ1. How do developers discuss security issues while using IoT techniques and tools?** Around 12% of questions and answers in our IoT dataset contain at least one sentence with discussions of security. The discussed security issues are multifaceted like involving the secure access/transmission of data, the configuration of secure communication among IoT devices, the diverse errors and incompatibilities IoT developers face while enforcing security principles across IoT devices, and so on.

**B. IoT ML Issues in Developer Discussions (RQ2)**

1) Approach: We use a set of keywords to identify ML-related sentences in the total 672,678 sentences of our 53K IoT posts. The keywords/phrases are: 1) machine learning,
TABLE II: Distribution of sentences & posts with ML discussions

| #Sentences | % Total | #Questions | % Total | #Answers | % Total |
|------------|---------|------------|---------|---------|---------|
| 801        | 0.12%   | 57         | 0.15%   | 8       | 0.06%   |

![Fig. 2: The ML-keywords used to find sentences discussion ML issues. The number for each keyword denotes the number of sentences have more than one of the seven search keywords/phrases. We discuss below each keyword/phrases with examples.](image)

1) **machine learning (465).** While we found majority of ML-related sentences using this phrase, many of these sentences also have one or more of the other keywords/phrases. In general, IoT developers discussed machine learning to train/fit ML models into their IoT devices. For example, this developer inquired about the feasibility of using Python scikit-learn library to train ML models into a Raspberry Pi2 (RPI2) device: “I am trying to utilize the Python library Scikit-Learn on my Raspberry Pi 2 for machine learning.”

2) **deep learning (104).** IoT developers discussed about training and embedding deep learning model with minimum hardware, so that the learned model could fit into IoT devices like Arduino: “I’m trying to feed my Raspberry Pi MPEG Video stream into an Ubuntu machine learning system called Darknet.”

3) **neural (240).** IoT developers asked diverse questions about the adoption of neural network-based ML models into their IoT devices. Such models can be the deep learning models or the ANN (Artificial Neural Network) models found in shallow learning libraries. IoT Developers inquired whether they could train a neural network model in a non-IoT device and then deploy the learned model into an IoT device: “i would like to train a neural network with tensorflow on my more powerful laptop and then transfer it to the rpi for prediction (as part of a magic mirror).”

4) **unsupervised learning (14).** The developers also inquired how the images and videos streams from their RPI2 device into a non-IoT device like a Ubuntu ML system: “I’m trying to feed my Raspberry Pi MPEG Video stream into a non-IoT device like a Ubuntu ML system:”

5) **reinforcement learning (20).** To overcome the low-computing resources in IoT devices that can be problematic for resource-intensive ML models, IoT servers or hubs (e.g., in Azure/Google cloud). Developers found it challenging to use such IoT servers for ML tasks, when the documentation is incorrect/incomplete: “According to https://docs.wso2.com/display/IoTS310/Analyzing+Data I should be able to do some Machine Learning tasks in IoT Server but the menu, usually available in WSO2 DAS, is missing, as is the Machine Learner features in “Configure->Features->Installed features” or “Configure->Features->Available features”.

6) **supervised learning (35).** The developers also encountered the floating point problem in their code while using neural network model: “I’m trying to calculate a neural network with this code below …The output goes by these value : -2.0422704 …but when I try to recalculate with matlab, the output goes by (this is the right one): 0.856575444075245 …My question is, is there something wrong with arduino and floating/double calculation which makes the calculation get wrong result?”

7) **adversarial (8).** IoT developers discussed about training and embedding deep learning model with minimum hardware, so that the learned model could fit into IoT devices like Arduino: “Currently I’m trying to replicate this wonderful project [https://www.youtube.com/watch?v=ia8pwmzUVx48] though with more minimum hardware, in which for the classification i’m using a neural network embedded inside the arduino uno which had been trained offline in more stronger PC.”

The developers also inquired how the images...
they are scanning using an IoT device can be fed into a deep learning model: “I'd like to feed the scanned images into a deep learning network, such that if I were to hold one or more of my cards in front of a camera, it would be able to identify which one(s) I was holding.”[Q2303587]Questions about the feasibility of using GPUs inside IoT devices are prevalent: “Can I use gpu for deep learning on raspberry pi 3?”[Q44381361]

**RQ2. How do IoT developers discuss machine learning issues and is there any overlap with security issues?**

Around 0.12% of the sentences in our dataset contained discussions about ML, which is considerably less than the security discussions we observed in our dataset. We also did not find any overlap between the ML and security discussions, i.e., IoT developers discussed security and ML-specific requirements in unrelated/different posts. The ML discussions ranged from using traditional shallow learning models to recent resource-intensive deep learning and neural network models. For deep learning, developers inquired about the feasibility of using GPUs inside their IoT devices as well as training the models in the cloud or in high-powered non-IoT devices and then deploying those trained models into their IoT devices. We also observed many tutorial-like discussions, where developers simply offered backgrounds like distinction between ML algorithm types. Therefore, IoT developers in SO are using the Q&A forum both to learn about their specific programming tasks involving ML models as well as to teach each other on the basics of ML domains/algorithms/platforms.

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**Implications.** The development and adoption of the IoT-based solutions by developers is facilitated by exponential growth of IoT devices, software, and platforms. Our increasingly interconnected digital world relies on smart devices built using IoT, which means security and ML adoption for IoT devices are paramount to leverage IoT-based solutions in wide-range of usage scenarios. The **IoT Vendors** need to support IoT developers with proper and usable secure IoT techniques. To determine what is appropriate and what is working, though, the vendors need to know the problems faced by IoT developers. Such insights can be crucial to the vendors not only to improve their offerings, but also to compare the solutions of their competitors. IoT vendors also need to make the IoT devices more usable for ML adoption. In particular, the deep neural network requires extensive computing resources, which IoT devices are often not equipped with. Our findings show that IoT developers are trying to make their IoT devices smart by adding ML-specific capabilities using deep learning models. However, they find it challenging to create a less resource-intensive versions of the ML models that can fit into their IoT devices. Recent attempts to create pre-trained language models (e.g., BERT [14]) offers hope to democratize deep learning models to low powered devices. More efforts are needed to make deep learning models usable for IoT devices. In addition, the deployment of an already trained model in IoT devices can be challenging due to the wide varieties of IoT devices. IoT vendors can take this as an opportunity to create container-based tools that do not have to rely on specific device configurations. **IoT Developers** can benefit from such techniques and tools to make their IoT-based devices smart and secure. IoT developers can also use our results to learn about the state-of-the-art in security and ML-adoption in IoT ecosystem. The **IoT...
Educators can develop tutorials and documentation to teach security and ML basics to IoT practitioners. The development and contents of such tutorials can be guided by the insights of developers’ problems discussed in SO. This is important because as we noted a large number of ML-related discussions in SO are simply basic tutorials like definitions of supervised and unsupervised ML, etc. The IoT Researchers can analyze the security and ML-adoption discussions to know about the specific challenges that IoT developers are facing based on their real-world experience. Such insights can be useful for the researchers to invent new techniques and tools, e.g., low-cost and less resource intensive ML models for IoT devices.

Threats to Validity. Internal validity threats relate to our bias while conducting the analysis. We mitigated the bias by using automated techniques to pick security and ML-related discussions. The security discussions are picked using a deep machine learning model that shows an F1-score of 0.92. The ML-related discussions are picked based on a set of keywords that denote the different types of ML algorithms. Construct validity threats relate to the difficulty in finding data to create our IoT security and ML-related sentences. While our data collection is based on automated approaches, we can miss relevant discussions that are not detected by our ML model to detect security or the discussions do not have any ML-specific keywords. However, our security detector model has high precision (0.92) and recall (0.93). Our ML-specific keywords also cover the different types of ML algorithms. External validity threats relate to the generalizability of our findings. Our findings are based on SO. A detailed analysis of security and ML-adoption based on developer discussions in other online forum is our future work.

VI. Related Work

Related work can broadly be divided into Studies to understand and Techniques to create smart and secure IoT tools.

Studies. Literature in IoT so far has focused on surveys of IoT techniques and architectures [2], [3], [35], [48], the underlying middleware solutions (e.g., Hub) [11], the use of big data analytics to make smarter devices [27], the design of secure protocols and techniques [2], [18], [24], [2] and their applications on diverse domains (e.g., eHealth [28]), the Industrial adoption of IoT [25], [43], and the evolution and visions related to IoT technologies [12], [31], [49]. The unauthorized inference of sensitive information from among IoT devices is a prevalent concern [8], [15], [22]. We are aware of no previous research that focused on understanding IoT security and ML discussions in SO.

Techniques. IoT devices can be easy target for cyber threats [18], [42], [52]. As such, significant research efforts are underway to improve IoT security. Automated IoT security and safety measures are studied in Soteria [9], IoTGuard [10]. Encryption and hashing technologies make communication more secure and certified [38]. Many authorization techniques for IoT are proposed like SmartAuth [39]. For smart home security, IoT security techniques are proposed like Piano [19].

VI. Conclusions

The rapid adoption of IoT-based solutions has necessitated the needs to develop proper security and machine learning (ML) techniques for IoT devices and communications. As such, it is important to understand the problems IoT developers discuss about their usage of security and ML tools and techniques in online technical forums like Stack Overflow (SO), which is one of the most popular online forums for software developers. We studied the security and ML-related discussions at the sentence level in a dataset of 53K IoT posts from SO. We find that IoT developers discuss problems related to security and ML adoption, with concerns and discussions about security are much more prevalent than ML-specific adoption. We find that security discussions can be multifaceted that can range from securing data access/storage/communication across devices and users as well as the incompatibilities of IoT devices with regards to the adoption of a security techniques/tools across platforms/devices. We also find that the resource constraints in the IoT devices make it challenging for IoT developers to adopt the recent advances in ML like deep learning models into the IoT devices. Our findings can offer insights to various IoT stakeholders like IoT vendors and researchers to improve the state-of-the-art practices of security and ML-specific adoptions across the diverse IoT ecosystems.

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