Security & Privacy in IoT Using Machine Learning & Blockchain: Threats & Countermeasures

NAZAR WAHEED, University of Technology Sydney, Australia
XIANGJIAN HE, University of Technology Sydney, Australia
MUHAMMAD USMAN, Federation University, Australia
MUHAMMAD USMAN, University of Surrey, UK

Security and privacy have become significant concerns due to the involvement of the Internet of Things (IoT) devices in different applications. Cyber threats are growing at an explosive pace making the existing security and privacy measures inadequate. Hence, everyone on the Internet is a product for hackers. Consequently, Machine Learning (ML) algorithms are used to produce accurate outputs from large complex databases. The generated outputs can be used to predict and detect vulnerabilities in IoT-based systems. Furthermore, Blockchain (BC) technique is becoming popular in modern IoT applications to deal with security and privacy issues. Several studies have been conducted on either ML algorithms or BC techniques. However, these studies target either security or privacy issues using ML algorithms or BC techniques, thus posing a need for a combined survey on efforts made in recent years addressing both security and privacy issues using ML algorithms and BC techniques. In this paper, we have provided a summary of research efforts made in the past few years addressing security and privacy issues using ML algorithms and BC techniques in the IoT domain. First, we discuss and categorize various security and privacy threats in the IoT domain that were reported in the past few years. Secondly, we classify the literature on security and privacy efforts based on ML algorithms and BC techniques in the IoT domain. In the end, various challenges and future research directions using ML algorithms and BC techniques to address security and privacy issues in the IoT domain are identified and discussed.

CCS Concepts: • Security and Privacy → Security services.

Additional Key Words and Phrases: Blockchain, cybersecurity, Internet of things, machine learning

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1 INTRODUCTION

We have seen the industries to evolve from manufacturing just the products to building the network of products known as the Internet of Things (IoT), and eventually creating an intelligent network of products [21]. As per Aksu et al. [4], two devices are connected to the Internet every three minutes.

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This connectivity and the exponential growth of IoT devices have resulted in an increased amount of network traffic. Due to this connectivity, challenges like security and privacy of user data and verification and authentication of devices, have arisen. For example, hackers compromised one billion yahoo accounts in 2013 [36]. In 2014, one hundred and forty-five million eBay users were under attack [77]. Following the increasing trend of attacks, in 2017, one hundred and forty-three million customers from Equifax had their personal information stolen [122]. Similarly, as reported in [54], a five billion dollar toy industry in 2017 had their eight hundred and twenty thousand client accounts compromised. It also included over two million voice recordings, out of which a few were held for ransom. The recent cyber history is full of cybersecurity disasters, from massive data breaches to security flaws in billions of microchips and computer system lock downs until a payment was made [35]. There is a plethora of security and privacy challenges for IoT devices, which are increasing every day. Hence, security and privacy in complex and resource-constrained IoT environments are big challenges and need to be tackled effectively.

The security challenges in IoT are increasing as the attacks are getting sophisticated day by day. Milosevic et al. [72] highlighted that powerful computing devices, e.g., desktop computers, might be able to detect malware using sophisticated resources. However, IoT devices have limited resources. Similarly, traditional cybersecurity systems and software are not efficient enough in detecting small attack variations or zero-day attacks [17], since both need to be updated regularly. Moreover, the updates are not available by the vendor in real-time, making the network vulnerable. Machine Learning (ML) algorithms can be used to improve the performance of cybersecurity systems. Based on the existing knowledge of cyber-threats, these algorithms can analyze network traffic, update threat knowledge database, and keep the underlying systems protected from new attacks [4, 113, 114]. Alongside using ML algorithms, the researchers have also started using revolutionary Blockchain (BC) technique to protect the underlying systems [29, 30, 56–58, 64, 82, 108, 121]. Although ML algorithms and BC techniques have been developed to deal with cyber threats in the IoT domain; a combination of these two is something new that needs to be explored.

Privacy goes hand-in-hand with security. Price et al. defined privacy as an application-dependent set of rules [81]. The authors elaborate that the rules on how the information can flow depend on the involved entities, and processes, frequency, and motives to access data, respectively. There are many applications, such as wearable devices [4], Vehicular Area NETwork (VANET) [119], health-care [123] and smart-home [24, 25, 98], that require providing security and protecting the privacy of personal information. For example, in a crowdsensing application like VANET, the network is dependent on the data collected from devices to make intelligent decisions on latest traffic conditions. However, the users of devices might be hesitant to participate due to inadequate privacy-preserving mechanisms and related threats. Extensive research works based on ML algorithms and BC techniques have been conducted in the past few years to protect data on devices and preserve user’s privacy, [4, 29, 30, 56–58, 64, 82, 108, 113, 114, 121].

**Paper collection:** The strategy of selecting articles for this study is depicted in Fig. 3. Initially, using the keywords and mentioned databases, the search was performed. The keywords such as IoT, Internet of Things, privacy, security, machine learning, and blockchain were utilized to download the latest articles from the top journals and conferences. The year-wise articles selection statistics are depicted in Fig. 4.

**Contribution of the paper:** This paper provides a detailed review of ML algorithms and BC techniques employed to protect IoT applications from security and privacy attacks. Based on the review, we highlight that a combination of ML algorithms and BC techniques can offer more effective solutions to security and privacy challenges in the IoT environment. To the best of our knowledge, this is the first paper that presents a review of security and privacy vulnerabilities in the IoT environment and their countermeasures based on ML algorithms and BC techniques. A
To cover the gaps in current literature (as summarized in Table 1), the major contributions of this paper can be summarized as follows.

- We provide generic classification of IoT threats reported in recent literature based upon security and privacy threats.
- We classify literature reviews on ML algorithms and BC techniques for IoT security and privacy, and highlight the research gaps in the existing literature reviews as in Tables 4, 5, 6 and 7.
- We provide a taxonomy of the latest security and privacy solutions in IoT using ML algorithms and BC techniques.
- We also identify and analyze the integration of ML algorithms with BC techniques to strengthen security and privacy in IoT.
- Finally, we highlight and discuss existing challenges to ML algorithms and BC techniques in IoT security and privacy with an attempt to suggest some future directions.

The rest of this paper is organized as follows. In Section 2, the classification of well-known IoT threats is presented. In section 3, we categorize literature reviews on IoT security and privacy using ML algorithms and BC techniques. Section 4 presents the latest solutions to IoT security and privacy threats, whereas research challenges for techniques based on ML and BC to solve security and privacy issues are presented in Section 5. Finally, in Section 6, we conclude by presenting the gaps with some future directions.

## 2 THREATS IN IOT

Threat exploits a vulnerability to perform an attack. The probability of an attack in a network increases with the network size. Therefore, the IoT network has more vulnerabilities than a traditional network, like, a company office. Additionally, IoT devices communicating with each
other are usually multi-vendor devices with different standards and protocols. The communication between such devices is a challenge, which requires a trusted third party to act as a bridge [13]. Moreover, several studies have raised the concern of regular software updates to billions of smart devices [33, 56].

The computational resources of an IoT device are limited, so the capabilities of dealing with advanced threats are degraded. To summarize, IoT vulnerabilities can be categorized as specific
For example, vulnerabilities like battery-drainage attack, standardization, and lack of trust are specific to IoT devices, and Internet-inherited vulnerabilities can be regarded as common vulnerabilities. Several IoT threats and their categorization have been introduced in the past [73, 84, 112, 114]. We discuss most common threats in IoT reported in the past decade and attempt to classify them into security and privacy categories.
2.1 Security Threats

The fundamental concepts of security and privacy revolve around the CIA triad of Confidentiality of the data, Integrity of data and Availability of network [14, 79, 118]. In IoT, data can be anything, for example, a user’s identity information, packets sent from a surveillance camera to destination server, a command given by a user to its car using a key-fob, or a multimedia conversation between two people. Any unauthorized disclosure of data may result in a violation of either confidentiality, integrity, or availability. If threat is impacting confidentiality, it is a privacy threat. The security threats affect both data integrity and network availability. These classifications are depicted in Fig. 5.

2.1.1 Denial of Service. Denial of Service (DoS) has comparatively the simplest implementation among all the security attacks. Furthermore, the ever-growing number of IoT devices with poor security features has made DoS a favorite tool for attackers. The core objective of a DoS attack is to ingest the network with invalid requests, which results in exhausting network resources, for example, bandwidth consumption. As a result, the services are unavailable to genuine users. Distributed DoS (DDoS) is an advanced version of DoS attack, where multiple sources attack a single target making it more difficult to trace and avoid the attack [1, 23, 90, 101, 102, 106]. Although there are different types of DDoS attacks, they all have the same objective. Few variants of DDoS attacks are SYN flooding [46] (in which an attacker sends successions of SYN requests to a target), Internet Control Message Protocol (ICMP) attacks [27] (in which large number of ICMP packets are broadcast using the victim’s spoofed IP), crossfire attacks [86] (using a complex and massively large-scale botnet for attack execution) and User Datagram Protocol (UDP) flooding attacks [50] (sending a large number of UDP packets to random ports on a remote victim). Botnet attack [74] is a type of DDoS attack in an IoT network. The botnet is a network of IoT nodes (devices) that are compromised to launch an attack on a specific target, for example, a bank server. Botnet attack can be executed on different protocols, particularly Message Queuing Telemetry Transport (MQTT), Domain Name Server (DNS), and Hypertext Transfer Protocol (HTTP), as briefed in [74]. Several techniques to prevent DoS in the IoT environment are suggested. Diro et al. [23] have utilized the self-learning characteristics of Deep Learning (DL) methods to detect an attack in the fog-things environment. In another study, Abeshu et al. [1] suggested controlling the DDoS attack by employing distributed DL on fog computing. Intrusion Detection System (IDS) by Tan et al. in [101, 102] is a series of research efforts to mitigate DDoS attacks using modern ML and DL algorithms. Sharma et al. and Tselois et al. [90, 106], respectively, pointed out the issues of flooding...
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in Software Defined Networks (SDN). The study highlighted that the SDN’s top layer was prone to brute force attacks due to the lack of authentication in the plain-text TCP channel.

2.1.2 Man-in-the-middle. Man-in-the-middle (MiTM) attacks are one of the oldest attacks in the cyber world [100]. Spoofing and impersonation can be categorized as MiTM attacks. For example, a node $X$ intending to communicate with destination $B$ might be communicating with the MiTM attacker, who is impersonating to be destination $B$. Similarly, in SSL striping, an attacker can capitalize on such attacks to connect themselves with the server using HTTPS connection, but with target on an unsecured HTTP connection. Recently, many studies have focused on improving the security against MiTM attacks [2, 7, 19, 109]. Ahmad et al. [2] discussed a healthcare scenario, where a patient gets an insulin dosage automatically. Such an application is vulnerable to MiTM attack, which can prove fatal. In line with the impersonation attacks, Chatterjee et al., [19] highlighted existing methods of authentication in wireless mobile devices that used a secret key. This key was saved in a non-volatile memory and used for digital signatures or hash-based encryption. Apart from being vulnerable, this technique was power inefficient. Similarly, the most recent and widely used IoT protocol, called OAuth 2.0, suffers from cross-site-recovery-forgery (CSRF) attacks. The OAuth protocol manually authenticates devices which is a time consuming process. Another study by Wang et al. [109] mentioned physical-layer security vulnerability in wireless authentication. They argued that the existing hypothesis test to compare radio channel information with channel record of Alice to detect a spoofer Eve in wireless networks, is often unavailable, particularly in dynamic networks.

2.1.3 Malware. Malware is an abbreviation of malicious software. With a growing number of IoT devices, it is becoming difficult to patch a software with the latest update. This opportunity may spur an attacker to install malware on a device and perform malicious activities. Malware is generally understood to exist as a virus, spyware, worm, trojan horse, rootkit, or malvertising [69]. Smarthome and healthcare devices, and vehicular sensors are a few examples that can be compromised. Azmoodeh et al. [9] studied malware in Internet of Battlefield Things (IoBT). Such attackers are usually state-sponsored, better-resourced and professionally-trained. Aonzo et al. [8], Feng et al. [32], and Wei et al. [111] attempted to defend resource-constrained android devices from malware attacks by using different supervised ML algorithms. Studies in [38, 56, 93] provided a detailed analysis of malware detection and highlighted several security loopholes in the Android platform, especially on the application layer, which has applications with several types of components.

2.2 Privacy Threats

In addition to security threats, IoT users and their data are prone to privacy attacks, such as sniffing, anonymization reverse, and inference attack. In any case, the impact is on the confidentiality of data, where data can be at rest or in motion. In this section, we discuss various privacy attacks.

2.2.1 MiTM. We believe that MiTM attacks can be classified into Active MiTM Attacks (AMA) and Passive MiTM Attacks (PMA). The PMA passively listen to data transfer between two devices. Although the PMA violate the privacy, they do not alter the data. An attacker with access to a device can silently observe for months before attempting the attack. With the growing number of cameras in IoT devices like toys, smartphones, and wristwatches, the impact of PMA, for example, eavesdropping and sniffing, is immense. On the other hand, the AMA are actively involved in abusing the data that are acquired by either interacting with a user pretending to be someone else, for example, impersonation, or accessing a profile without consent, for example, authorization attack.
2.2.2 Data Privacy. Similar to MiTM attacks, the data privacy attacks can be classified into Active Data Privacy Attacks (ADPA) and Passive Data Privacy Attacks (PDPA). Data privacy is related to data leakage, data tampering, identity theft, and re-identification. The re-identification attacks are also known as inference attacks and are based on de-anonymization attacks, location detection, and aggregation of information. In these attacks, the main goal of a hacker is to gather data from multiple sources and reveal personal identities of targets. Some attackers may use the collected data to impersonate an individual target. Any attack that alters data, such as data tampering, can be classified as ADPA, while, the re-identification and data leakage are examples of PDPA.

A comparison between various security and privacy threats, their types, their impacts, and possible solutions are summarized in Tables 2 - 3.

Table 2. Security threats in IoT

| Threat          | Impact        | Attack     | Type                | Layer of Impact | Solution                        |
|-----------------|---------------|------------|---------------------|-----------------|---------------------------------|
| Security        | Availability  | DoS        | Flooding            | Physical, MAC   | Multiple                         |
| Physical        |               | DDoS       | Physical, MAC       | Multiple        |                                 |
| Injury          |               | Botnet     | Physical, MAC       | Multiple        |                                 |
| Physical Damage |               | Damage     | Physical            | Physical Security|                                |
| Environmental   |               | Power Loss | Physical            | Shielding       |                                |
| Hardware Failure|               | Tampering  | Physical            | Backup          |                                |
| Integrity       |               | MiM        | Sybil Attack        | Physical, MAC,  | code attestation, radio resources testing, key pool |
|                 |               |            | Network             | Network         | anti-spoofing software         |
| Malware         |               | Injection  | Application         |                 |                                 |
|                 |               | Virus      | Application         |                 |                                 |
|                 |               | Worms      | Application         |                 |                                 |

Table 3. Privacy threats in IoT

| Threat          | Impact        | Attack     | Type                | Layer of Impact | Solution                        |
|-----------------|---------------|------------|---------------------|-----------------|---------------------------------|
| Privacy         | Confidentiality| MiM        | Eavesdropping       | Network         | Encryption                      |
|                 |               | Impersonation| Network            | Encryption      |                                 |
|                 |               | Sniffing    | Network             | Encryption      |                                 |
| Data Privacy    | Authorization | Application| Application        | Access Control  |                                 |
|                 | Re-identification| Multiple  | Multiple            | data suppression, generalization, noise addition | |
|                 | Data Leakage  | Multiple    | Multiple            | anonymization   |                                 |
|                 | Re-identification| Multiple  | Multiple            | anonymization   |                                 |
|                 | Data tampering| Multiple    | Multiple            | Use TLSv1.2      |                                 |
|                 | Identity Theft| Transport   | Transport           |                 | Turn off export ciphersuite options in browser | |
|                 | Poodle        | Transport   | Transport           |                 |                                 |
|                 | Heartbleed     | Transport   | Transport           |                 |                                 |
|                 | Freak          | Transport   | Transport           |                 |                                 |

3 LITERATURE SURVEY

This section provides an existing literature review and categorizes the efforts done based on ML algorithms and BC techniques to address IoT security and privacy issues. This section is divided into two subsections, i.e., ML algorithms and BC techniques.
3.1 Machine Learning Algorithms

Hackers are getting sophisticated with the evolving technology, making traditional methods of attack-prevention cumbersome. The defense becomes more challenging for a resource-constraint IoT device. To help detect these attacks, one of the widely used tools is ML algorithms. Several ML algorithms have proven extremely helpful in mitigating security as well as privacy attacks. In regard to this, various literature reviews on ML-based approaches addressing IoT security and privacy issues are summarized in Tables 4 and 5. In the following subsections, we discuss these approaches in detail.

3.1.1 Security Efforts. The technology has improved data communication and networking techniques over the Internet. We have now state-of-the-art software-based configurable devices called Software Defined Network (SDN) that can be customized to meet a customer’s needs. In this scenario, Restuccia et al. [84] attempted to present the taxonomy of existing IoT security threats and their solutions in SDN using the ML algorithms. They also suggested that since the main task of an IoT system is to collect data from IoT devices, it is feasible to divide the data collection process into three steps, namely IoT authentication, IoT wireless networking, and IoT data aggregation & validation. The study gave a brief review of ML algorithms used to mitigate the security attacks, e.g., to detect cross-layer malicious attacks, Bayesian learning is used, and to assess the validity of data, neural networks are used. However, the study lacks an in-depth analysis of the rest of the ML algorithms.

In today’s modern digital communication world, security threats are in various forms. One of the most difficult to detect security threat is Insider attack. Insider attacks are usually attributed to employees of an organization. Liu et al. [62] have provided a detailed survey on such attacks. The authors categorized threats into multiple categories, i.e., traitor, masquerader, unintentional perpetrator, and data infiltration. In these categories, the most common threat is data infiltration, i.e., a violation against data integrity and availability and sabotaging the underlying system. This study distributes data sources into multiple categories, i.e., host-based, network-based, and contextual data sources. In each category, a comprehensive comparative analysis of the existing schemes and systems is also provided. Liu et al. [62] suggested that the most researched defense technology is an IDS using ML algorithms. However, the study only discussed insider security threat, while our survey is much comprehensive.

In another work [115], the authors explained in detail how the latest ML and DL algorithms could be used for cybersecurity. This study provides a general overview of several algorithms that are used in different IDS along with their limitations. Similar to this, a survey on ML and data mining algorithms for IDS is presented by Buczak et al. [15], based upon the most-cited emerging methods, e.g., Artificial Neural Network (ANN), Association Rules and Fuzzy Associations Rules, Bayesian Networks (BN), Clustering, Decision Tree (DT), Ensemble Learning, Evolutionary Computation, Hidden Markov Model (HMM), Inductive Learning, Naive Bayes (NB), Sequential Pattern Mining and Support Vector Machine (SVM). The datasets and algorithms are discussed in terms of their functionalities and complexities. The researchers [15] have pointed out the peculiarities of the ML algorithms for cybersecurity and suggested improvements; however, their study is dedicated to wired network intrusion detection. In a wired network, an intruder has to pass multiple layers of firewall and operating system, while, a wireless network is comparatively more vulnerable.

Correspondingly, Mishra et al. [73] suggested that an IDS trained for one particular scenario may not be as effective in another. Their study provided a comprehensive comparison of various situations. The attacks like Remote-to-Local (R2L) and User-to-Root (U2R) have a fewer number of samples in benchmark datasets. These low-frequency attacks are difficult to detect by an ML-based model. Apart from suggested improvement on detection of low-frequency attack, the study
Table 4. Existing surveys on IoT security Using Machine Learning algorithms

| Ref. | Use Case | Security Threats | Solutions |
|------|----------|------------------|-----------|
| [84] | SDN      | Authentication, Data aggregation | Detailed IoT framework |
| [62] | Network  | Traitor, masquerader & perpetrator | Comprehensive analysis of threats & their stepwise execution. |
| [115] | IDS      | Anomaly, Signature, Hybrid | Detailed technical survey on the latest ML/DL algorithms |
| [13]  | IDS      | Anomaly, Signature, Hybrid | Focused survey on ML & DL for IDS |
| [73]  | Network  | DoS, R2L, U2R, Probe | Analysis of ML algorithms and choosing a suitable one |
| [93]  | Industrial IoT | Malware Threats | Analysis of malware detection for Android mobile |
| [16]  | 802.11   | WEP related      | Analysis of infrastructure-mode network-based attacks secured by WEP |

further classified the cyber-attacks based on their characteristics. The main contribution of this survey is the classification of the ML algorithms into four categories and then comparing the relevant algorithms in each group. For single classifier with all features, the algorithms compared were DT, Neural Network, NB, SVM, and Fuzzy Association. Secondly, for single classifier with limited features, the compared algorithms were DT, Hidden NB, Mutual Information-based Feature Selection (MMIFS) with SVM, and Cluster Centre and Nearest Neighbor (CANN). For multi-classifier with all features, the analyzed algorithms were ASM (an ensemble of ANN, SVM, and MARS), FC-ANN, Neuro-Fuzzy, Multi-NN, CT-SVM, CSVAC, and an ensemble of ANN and EN. Finally, for the fourth type, i.e., multi-classifier with limited features, the analyzed algorithms were SVM, DT, SA, FPSO, and k-means (to name a few). However, similar to [15], Mishra et al. [73] is restricted to the wired networks, and their attack dataset is network-based.

Sharmeen et al. [93] aimed to assist application developers in using Application Program Interfaces (APIs) safely, during the development of applications for Industrial IoT networks. The authors suggested that to detect malware; the ML model can be trained by using three types of features; static, dynamic, or hybrid. A detailed analysis of each feature type is done using performance metrics of a dataset, features extraction technique, features selection criteria, accuracy, and detection method. Several detection methods for each feature set were analyzed, but the commonly used were RF, SVM, KNN, J48, and NB. Sharmeen et al. [93] concluded that hybrid analysis offered flexibility in choosing both the static and dynamic features to improve accuracy in the detection process. However, this paper is limited to one application (android device) and one security threat (malware).

In another work, Kolias et al. [16] gathered, categorized, and thoroughly analyzed well-known attacks on the 802.11 network. Authors proposed three categories of attacks for 802.11 network, i.e., purpose, target and methodology. The study provided a comprehensive evaluation of eight ML algorithms using the features from AWID dataset. Among AdaBoost, Hyperpipes, J48, NB, OneR, RF, Random Tree (RT), and ZeroR, the best performing classifier on 156 features set was J48. Another interesting analysis of this survey was the performance comparison of these algorithms on separate classes. The best performer in each class was as follows: OneR for benign traffic has 99.9% accuracy. NB for flooding attacks has 72.69% accuracy. J48 for injection attacks has 99.98% accuracy. The toughest to recognize was the impersonation attack in which RT performed the rest by achieving 7.5% accuracy. However, the study was focused on 802.11 networks only, and considering a single benchmark dataset as a source may yield biased results.

All of the above papers, as depicted in Table 4 were limited to security threats with a focus on a specific use case. Moreover, they used only ML as a tool in solving the security issues, while our paper covers a broader scope as depicted in Fig. 2.

3.1.2 Privacy Efforts. Machine Learning extracts useful information from the raw data, while privacy is preserved by concealing the information [44]. According to Al-Rubaie et al. [5], ML system has three modules: input, computation, and output. The output is a result which is calculated
Table 5. Existing surveys on IoT privacy using Machine Learning algorithms

| Ref. | Use Case       | Privacy Threats          | Solutions                                      |
|------|----------------|--------------------------|------------------------------------------------|
| [112]| MCS            | Impersonation            | Several DL approaches are presented            |
| [83] | Network        | Surveillance, Information leakage | k-anonymity, l-diversity, t-closeness, randomization |
| [5]  | Network        | Reconstruction, inversion, inference | HE, GC, secret sharing & secure processors     |
| [76] | ML             | injection, modification, tampering | Defense at each point of an ML model            |
| [65] | Network        | Inversion, Eavesdropping, reverse engineering | Defensive mechanism for each attack.            |
| [120]| Social Network | De-anonymization         | Anonymization techniques                       |
| [107]| Cloud          | Data Leakage             | Data reduction, sanitizing, encryption.         |

by the computational module when the input data is fed to it. Al-Rubaie et al. [5] claimed that privacy could only preserve if all three modules were under the ownership of a single entity. Nowadays, the data is collected by billions of IoT devices such as smart-phones, health monitoring sensors, speed cameras, and temperature sensors; hence a single-ownership condition is violated. This issue spurred interest in researchers to work towards proposing newer and improved privacy-preserving ML algorithms. In this section, we highlight some of the latest surveys in this domain.

Everyone uses global positioning system maps for their daily commute, which needs continuous improvements. The most effective and useful data for such applications is collected from the users directly by using the technology called Mobile CrowdSensing (MCS). Xiao et al. [112] reviewed the privacy threats involved in MCS, where the information of interest is extracted, and the participants upload sensing reports of their surrounding to the MCS server. This information-sharing poses significant privacy threats to the participants and the MCS server. The system is prone to privacy leakage (which is related to user’s personal information), faked sensing attacks (sending fake reports to the server to reduce the sensing efforts) and advanced persistent threats (causing privacy leakage over an extended period). The survey suggested Deep Neural Network (DNN) and Convolutional Neural Network (CNN) for privacy protection, and Deep Belief Network (DBN) and Deep Q-Network (DQN) for counter-measuring faked sensing. However, the review was limited to only one application (MCS).

In a survey by Rao et al. [83], privacy threats in data analytics, privacy preservation techniques, and their limitations were examined. The authors blamed smartphone users in contributing to data leakage by blindly accepting the privacy policy of an application. These vulnerabilities exposed the users to privacy threats like surveillance (recommendations of new friends, places to visit, people to follow; by continuously monitoring a customer’s transactions), disclosure (revealing customer’s information without his consent), discrimination (having a biased opinion for someone), and personal embarrassment (disclosing a customer’s information resulting in his abuse). Later in the survey, Rao et al. [83] comprehensively analyzed different privacy preservation methods. The data was modified to preserve privacy before being sent for analysis. This technique is called Anonymization and has several types, including k-anonymity, l-diversity, and t-closeness. K-anonymity cannot guarantee identity privacy since it is prone to homogeneity and background knowledge attack [67]. L-diversity was introduced to address the homogeneity attacks; however, it is likely to skewness and similarity attacks. Moreover, its practical implication becomes difficult in a variety of data. Few algorithms in this direction were explained by Tripathy et al. [103, 104]. t-closeness is an improvement to l-diversity and attributes privacy is ensured. However, data distribution is not guaranteed every time. For a detailed study, the survey on anonymization attacks [22], and their counter-measuring algorithms [91, 120] are worth a read. The second category of the technique discussed by Rao et al. [83] is the process of adding noise to the data, called Randomization. It has several advantages over Anonymization. Firstly, the loss of information due to Anonymization is avoided. Secondly, there is no anonymization overhead. However, Rao et al.
have proved that implementing Randomization on a large data set is not efficient as it increases the computation time and complexity. Sequel to privacy-preserving techniques categorization, i.e., the third technique, is data distribution, which is done either horizontally or vertically. Horizontal distribution refers to the data being distributed across multiple sites under the same organization, while vertical distribution applies to an entity’s information distributed across various sites under different organizations. In the type of horizontal distribution, distribution of data could be done by classification and clustering algorithms; however, it does not ensure privacy. Similarly, the vertical distribution of data also cannot guarantee confidentiality if the datasets are shared. Therefore, Rao et al. [83] concluded that although the distribution of data did not ensure privacy, it was closely related to cryptographic techniques. One of the privacy-preserving methods covered in many studies is differential privacy. The limitation of differential privacy is that it is only useful when the two data items are under separate ownership. In the end, the authors highlighted that Multidimensional Sensitivity Based Anonymization (MDBSA) was an improved version of Anonymization and was the most effective since it could accommodate complex and voluminous data and still preserved the attributes. However, MDBSA achieves all of this at the cost of accuracy.

In another latest survey, Al-Rubaie et al. [5] argued that the user data collected by several companies for data analysis is vulnerable to several threats. Anonymity techniques do not necessarily offer complete privacy since the attacker can extract the required information based on the output data. The authors explained that any ML task was comprised of three modules, i.e., input, computation, and output. If one owner operates all modules, then the privacy is preserved, but unfortunately, that is not the typical case. Such a system is therefore prone to several attacks such as reconstruction (information extraction from raw data), model inversion (utilizing the confidence information), and membership inference (finding particular target information). The authors have suggested solutions to all of the attacks. For example, ML models like SVM that stores explicit feature vectors should be avoided to counter the reconstruction attacks. Model inversion attack can be avoided by using sophisticated and random dataset. The restrictions on the output to the class label are the most effective to counter membership inference as proved by Shokri et al. [96]. The authors highlighted that such solutions were obtained by utilizing either cryptographic approaches (Homomorphic Encryption (HE), garbled circuits (GC), secret sharing, and secure processors) or Differential Privacy (DP) techniques (input, algorithm, output, and objective perturbation).

Papernot et al. [76] articulated a comprehensive threat model for privacy-preserving ML algorithms, and taxonomized attacks and defensive techniques within an adversarial framework. Considering the life-cycle of an ML-based system from training to inference, the authors explained the strength of an attacker at different points. For example, an attacker with the knowledge of only the features at a training-level is considered weaker as compared to someone who knows the algorithm and the input dataset. The attacks were divided on the basis of the point of impact at different stages of an ML model, and hence had, for example, training-time attacks (poisoning and inversion) and inference-time attacks (integrity and exploratory attacks). The work also provides a review on how to safeguard the user data by differential privacy (and its variants). At the training stage, several techniques such as randomized-response, objective perturbation, multi-party computations, and stochastic gradient descent were reviewed to protect user’s response to server queries. Since the differential privacy degrades the accuracy of predictions at the inference stage, it is recommended to use a variant of homomorphic encryption which however has a limitation of increased performance overhead. Similarly, Liu et al. [63] have discussed privacy threats in an ML model, such as inversion attack, eavesdropping, and reverse engineering. The authors highlighted the importance of data privacy and their vulnerability in the scenario of data leakage. To avoid this, multiple cryptographic technologies, such as differential privacy and homomorphic encryption,
are suggested to be used to protect data privacy. However, the focus of the study is limited to the end-user and edge-computing rather than cloud computing.

In yet another literature, [120], a systematic review of anonymization techniques for privacy-preserving in the social network application is done. The authors have categorized social network data problems into privacy, background knowledge, and data utility. Furthermore, privacy preservation anonymization methods are categorized as clustering-based and graph-modification approaches. The clustering-based method achieves privacy by clustering the vertices and edges into groups while anonymizing the sub-graph into a super-vertex. It has four sub-categories: vertex, edge, vertex & edge, and vertex-attribute mapping. On the other hand, the graph modification method modifies the edges and vertices in a graph to attain anonymization. Three possible ways to do it are Optimization, Randomization, and Greedy Graph Modification. The authors have explained the algorithm of all of these techniques. Apart from being more than ten years old, the literature, however, has not mentioned the names of any particular benchmark scheme to be used in ML algorithms. In a similar context, a more recent and comprehensive survey is conducted by Sharma et al. [91]. After classifying the anonymization techniques into clustering, clustering with constraints, modification, and hybrid, the authors have explained the anonymization algorithms for k-anonymization (k-degree, k-n neighborhood, p-sensitivity k-anonymity, and l-diversity k-anonymity), and randomization (random edit technique, and random switch edges). However, these techniques are limited to a single domain of social network data.

Wang et al. argues that the daily increase in multimedia data in many applications, such as video streaming and video conferencing, is increasing the time required for its processing and transmission [107]. In addition to that, it has increased irrelevant and redundant data. Many organizations are outsourcing their processing-intensive tasks to avail faster and cheaper cloud-computing options. As a solution to these issues, several researchers used data-reduction techniques, which send fewer data to the cloud. Such features extraction techniques can not only reduce the data and its transmission time but also preserve some privacy as some information is hidden. Other than discussing the state-of-art privacy-preserving schemes and their design challenges, this paper reviewed outsourcing schemes with an emphasis on secure multi-party computation (SMC) and homomorphic encryption (HE) [107]. The discussed systems are comprehensively analyzed using performance metrics like security, effectiveness, and efficiency.

### 3.2 Blockchain

Blockchain, often confused by some as a synonym to bitcoin, is the technology behind this infamous crypto-currency. It is a distributed ledger which stores the data in blocks. These blocks are in order and linked with each other cryptographically forming a chain in a way that makes it computationally infeasible to change the data in a particular block [18]. This mechanism ensures immutation, decentralization, fault-tolerance, transparency, verifiability, audit-ability, and trust [20]. Several reviews and survey papers are published to highlight the importance of the BC technique [10, 20, 26, 33, 51, 53, 59, 69, 71, 85, 105, 117]. A detailed comparison of current work is shown in Table 6 and 7. Most of these works discussed either security or privacy issues. In this section, we present the current literature reviews on achieving security and privacy in IoT using BC techniques as a tool.

#### 3.2.1 Security Efforts

Security has been the prime focus of attention for any IoT uses cases. Lots of work based on BC techniques have emerged to solve security issues in the IoT domain. A study on IoT security was presented by Banerjee et al. [10], which is classified into security techniques such as intrusion detection and prevention system (IDPS), collaborative security, and predictive security. Furthermore, IDPS are classified by approaches, network structure, and applications. After that,
Table 6. Existing surveys on IoT security using blockchain techniques

| Ref. | Use Case | Security Threats | Comments |
|------|----------|------------------|----------|
| [10] | IoT      | Several          | Classified post 2016 literature & discussed BC-based solution |
| [51] | IoT      | key management, access control | Categorization of threats & their BC-based solution. |
| [85] | IoT      | DoS              | IoT Vision |
| [71] | Network  | data sharing     | A review on the application of BC to intrusion detection. |
| [53] | IoT      | identity theft, access control | BC based suggestions are given |

collaborative security and predictive security are discussed in detail. In the same study, collaborative security techniques are classified by network structures and applications. Sequel to this study, the integrity of existing IoT datasets is highlighted, and the authors suggested that a BC-based standard should be developed to ensure integrity in the shared datasets.

In another study by Khan et al. [51], security issues related to key management, access control, and trust management in IoT are discussed. Khan et al. [51] categorized the security threats into IoT layers and presented their BC-based solutions. The IoT security issues were classified as low-level, intermediate-level, and high-level security issues. Khan et al. [51] believes that jamming adversaries, insecure initialization, spoofing, vulnerable physical interface, and sleep deprivation attacks are the low-level security issues. Whereas, replay, RPL routing attacks, sinkhole, Sybil attack on intermediate layers, transport-level end-to-end security, session establishment, and authentication are intermediate-level security issues. The high-level security issues are insecure interfaces, CoAP security with internet, vulnerable software, and middleware security. The study then provided a comprehensive mapping of all the above problems with the affected layers of IoT architecture and proposed solutions for each one of them. In the end, the authors discussed how BC techniques could be used to address and solve some of the most pertaining IoT security problems. This survey highlighted the security risks involved in each IoT layer but lacked the discussion of providing BC-based solutions for these security threats.

Similarly, Reyna et al. in [85] analyzed how BC techniques could potentially improve the security (data reliability) in the IoT. The study mentioned security threats as one of the challenges for BC techniques. The security threats mentioned in the study were majority attacks, double-spend attacks, and DoS attacks. The study also provided highlighted about the integration of IoT with BC techniques, BC applications and platforms was done. However, the study did not cover several other security attacks related to IoT, which was a limitation of this survey.

To enhance the capabilities of IDS, the researchers in [71] reviewed the collaborative IDS (CIDS) using BC techniques. For IDS, to work collaboratively, two main issues were of data sharing and trust computation. The review highlighted several questions and attempted to provide their solutions using the BCs. The challenges for IDS highlighted in [71] were overhead traffic with limited handling capability, limited signature coverage, inaccurate profile establishment, and massive false alerts. For BC techniques, the limitations are energy and cost, latency and complexity, regulations and management, security and privacy, organization and size, and the awareness and adoption. The literature reviewed applications of BC techniques for intrusion detection but mainly lacked the details of the consensus protocols used in the latest BC techniques.

A table of the existing surveys focused on security using BC techniques for IoT applications is compiled in Table 6.

3.2.2 Privacy Efforts. The review by Kshetri et al. [53] compared cloud-based solutions with BC techniques to preserve privacy in an IoT environment. It highlighted the challenges, such as identity management and access control systems, for existing cloud-based solutions, and suggested BC-based alternate as their solutions. The study demonstrated how an attack in IoT could be contained
Table 7. Existing surveys on IoT privacy using blockchain techniques

| Ref. | Use Case | Privacy Threats          | Comments                                           |
|------|----------|--------------------------|---------------------------------------------------|
| [53] | IoT      | Identity management      | BC-based solutions                                 |
| [88] | Network  | Confidentiality          | Issues in traditional schemes                      |
| [55] | IoT      | Spoofing, authentication | IoT security and privacy issues and how BC can be a solution |

using BC techniques. However, a comprehensive threat model for privacy-preserving in IoT using BC techniques was missing in this literature. Similar to this, Salman et al. [88] focused on the use of privacy-preserving BC techniques. They highlighted data-privacy mechanisms, such as encryption, public-key cryptography, and access control. The study discussed traditional schemes, such as access control lists (ACL), public-key identity (PKI), and Identity Based Cryptography (IBC), highlight their challenges, and suggested their blockchain-based solutions. However, the paper did not discuss some of the latest privacy techniques, such as data anonymization and differential privacy. Moreover, the study did not discuss the issues of BC techniques as a privacy solution in an IoT environment.

In another study [52], the authors highlighted the privacy issues in IoT and provided their BC-based solutions. As per the research, the main goal of privacy-preserving techniques was to attain a trio of anonymity, unlinkability, and intractability. Furthermore, they addressed the privacy of data and user’s behavior in the IoT and discussed their solutions, for example, data tagging, zero-knowledge proof, and k-anonymity model. Along with it, the benefits of BC techniques and their challenges were mentioned. The authors discussed the issues of data-sharing and highlighted their BC-based solutions. However, the literature did not provide a detailed study on privacy issues and threats related to IoT, nor did it provide any practical solution to preserve privacy using BC.

4 SOLUTIONS TO IOT THREATS

Since the inception of the first virus (Creeper) in 1970 until the hack of Whatsapp on 15th May 2019 and later, security specialists have mitigated zero-day security or privacy threats. In regard to this, there are many solutions in several studies however, this section focus on the latest IoT security and privacy solutions. We first discuss the solutions offered by using ML algorithms as a tool, then by utilizing BC techniques, and finally by the fusion of both.

4.1 Existing Solutions Using Machine Learning Algorithms

ML is used as a data processing pipeline in any framework. For example, data traffic entering a network can be analyzed by an ML model to make an informed decision. The main components of ML threat model for IoT are shown in Fig. 6. Additionally, the figure gives an overview of target points, such as input and output, for an attacker. The input data from source to IoT nodes, and IoT nodes to ML model can experience exploratory or poisoning attacks. At the output, integrity and inversion attacks are possible [63]. Therefore, for a whole system to be completely immune to attacks, it must be secured as well as privacy-preserved.

4.1.1 Security efforts. Several security solutions have been proposed using ML algorithms as a tool, as shown in Table 8. To deal with the flooding attacks, Diro et al. [23] argued that fog-computing reduced the risk of eavesdropping and MiTM attacks by restricting the communication to the proximity of IoT devices. Capitalizing on this idea, they used Long Short Term Memory (LSTM) algorithm in their model as it can remember the older data. For binary classification, they compared their results with LR using ISCX2012 dataset, which had 440,991 normal traffic instances and 71,617 DoS attack instances. The DL model LSTM took considerably more time to train than LR, but its
accuracy was 9% better. The second dataset used was AWID from [16], and consists of normal traffic instances (1,633,190 training and 530,785 tests), injection attack instances (65,379 training and 16,682 tests), flooding attack instances (94848 training and 8097 tests) and impersonation attack instances (48,522 training and 20,079 tests). After comparing LSTM against softmax for multi-class classification, the resultant accuracy obtained was 14% improved.

In a similar study, Abeshu and Chilamkurti highlighted that the resource constraints of an IoT device made it a potential threat to DoS attacks [1]. Classic ML algorithms are less accurate and less scalable for cyber-attack detection in a massively distributed network such as IoT. Such a massive amount of data produced by billions of IoT devices enable the DL models to learn better than the shallow algorithms. The authors of [1] argued that most of the employed DL architectures had used pre-training for feature extraction, which could detect anomalies and thus reduced the workload of a network administrator. However, their work was focused on distributed DL through parameters and model exchange for the applications of fog computing. Fog computing reduced the load of computing power and storage space from the IoT devices. It is, therefore, the ideal spot where an intrusion can be detected. The existing Stochastic Gradient Descent (SGD) for fog-to-things computing needs parallel computing. Thus, the centralized SGD will choke due to the massive amount of data in IoT. Therefore the study proposed a distributed DL-driven IDS using NSL-KDD dataset, where the stacked auto-encoder (SAE) was used for feature extraction, and soft-max regression (SMR) was used for the classification. Their study proved that the SAE as a DL worked better than traditional shallow models in terms of accuracy (99.27%), FAR and DR. Both Diro et al. [23] and Abeshu et al. [1] proved that the DL algorithms performed better than shallow ML models.

As a first attempt to DoS detection, Tan et al. [101] used triangle-area-based technique to speed up the feature extraction in Multivariate Correlation Analysis (MCA). Features were generated to reduce the overhead, using the data that entered the destination network. Along with this, the "triangle area map" module was applied to extract the geometrical correlations from a pair of two distinct features to increase the accuracy of zero-day attack detection. In an attempt to improve their results from [101], Tan et al. [102] used Earth Mover’s Distance (EMD) to find the dissimilarities between observed traffic and a pre-built normal profile. The network traffic was interpreted into images by feature extraction using MCA and analyzed to detect anomalies using KDDCup99 and ISCX datasets. Using the sample-wise correlation, the accuracy of their results obtained was 99.95% (KDD) and 90.12% (ISCX). However, the study neither revealed the data size nor the effects of varying sample sizes. Moreover, MCA assumed the change to be linear, which was not a realistic approach. Another form of DoS attack in IoT is called a botnet attack, which was explained earlier in Section 2. To prevent botnet attack against HTTP, MQTT, and DNS, the authors of [74] developed an IDS, which is an ensemble of DT, NB, and ANN. Since the correntropy values of benign and malicious vectors were too close, it was decided to use DT, NB, and ANN as they could classify such vectors efficiently. The performance metrics were detection-rate and false-positive rate, for which, their proposed ensemble was better than every individual algorithm in that ensemble. For the datasets of UNSW and NIMS, the accuracies achieved were 99.54% and 98.29%, respectively.

Similar to DoS attacks, the MiTM attacks are one of the most frequently occurring attacks in an IoT network. In regard to this, a lot of technical solutions have been proposed for several applications. The authors [2] have used LSTM RNN to prevent the impersonation attacks in a smart healthcare scenario, since traditional feedforward neural networks cannot capture the sequence and time-series data, due to their causal property. Moreover, the researchers solved the vanishing gradient issue of RNN algorithm and improved accuracy. At first, the predicted value was calculated based on the dataset log of three months (for a patient who is taking insulin injections). If the
predicted and calculated values differed for more than a certain threshold, then by using the combination of DL and gesture recognition, the correct dosage was ensured. However, the detail of the model and analysis was missing in their work. Similarly in another scenario to prevent the impersonation attacks, the authors of [19] utilized Physical Unclonable Function (PUF), which is an inherent characteristic of silicon chip that is unique and can be used as a basis of authentication in RF communication. During the manufacturing phase, every transmitter inherits some unique features called offset from an ideal value. The authors have used these offsets as their features to recognize the device, train their system on it, and then detect the accuracy. Using ANN MATLAB toolbox, the performance metrics were calculated. With the help of ML, the simulation results could detect 4,800 nodes transmitters with an accuracy of 99.9% and 10,000 nodes under varying channel conditions, with an accuracy of 99%. The proposed scheme can be used as a stand-alone security feature, or as a part of traditional multi-factor authentication. PUF is inherent and inexpensive and can significantly benefit IoT, wherein each wireless sensor’s physical values can be stored in a secure server replacing traditional key-based authentication. However, the authors in their approach have assumed the server storing the PUF values is safe. Aminanto et al. used an unsupervised ensemble of ML algorithms using SVM, ANN, and C4.5 for feature extraction and ANN as the classifier [7]. In their process of deep-feature extraction and selection (D-FES), first, they used SAE to extract the features, then SVM, ANN, and C4.5 were used for feature selection, and finally, ANN was used to classify. The study achieved an accuracy of 99.92% by using AWID dataset, on which an earlier study by Kolas et al. [16] had the worst accuracy for impersonation attack.

According to Statista [28], mobile phone users would reach close to three billion by year 2020. This increase in usage made mobile phone vulnerable to the malware attack [8, 9, 32, 93, 110, 111]. Azmoodeh et al. [9] believed that OpCodes could be used to differentiate benign-ware and malware. Class-wise Information Gain (CIG) is used for feature selection because the global feature selection causes imperfections, and even reduce system efficiency especially when the dataset is imbalanced. They also claimed that this combination of OpCode and DL for IoT had never been explored. Using Eigenspace and deep convolutional networks algorithms, 99.68% accuracy was achieved, with precision and recall rates of 98.59% and 98.37%, respectively. Similarly, to mitigate malware, Wei et al. [111] extracted the features using the dynamic analysis technique. They used application functional classification to train the classifier for clean and malicious data, while, in the testing phase, kNN was used to divide data into known categories. J48 decision tree and NB were used to perform 10-fold cross-validation. Depending on the performance metric, the study claimed 90% accuracy.

Contrary to dynamic analysis[111], the authors of [8] used static analysis techniques for feature extraction considering all the Application Platform Interfaces (API) that were not studied previously. Feature selection was made manually based on the most-used features by the previous researchers. They claimed the accuracy of 98.9% with the second biggest malware testbed dataset ever used. As the intrusion techniques were getting sophisticated, the static analysis became invalid, and it was therefore required to use a dynamic scheme [32]. With the static analysis techniques, the attackers adopted deformation technologies, which could bypass the detection while dynamic analysis methods were promising due to its resistance of code transformation techniques. The authors of [32] proposed a new framework, called EnDroid, based on these issues. The proposed model used "Chi-Square" for feature extraction, five different algorithms (decision tree, linear SVM, extremely randomized trees, random forest & boosted trees) as an ensemble for base-classification, while LR was used as meta-classifier. For the dataset, a combination of "AbdroZoo" and "Drebin" datasets was utilized so that an accuracy of 98.2% was achieved. Wang et al. argued that most of the existing literature on malware detection was based on static string features, such as permissions and API usage extracted from the apps [110]. However, since malware had become sophisticated,
using a single type of static feature might result in a false-negative. In their proposed model - DriodEnsemble, a fusion of string and structural features was utilized to detect Android malware. Using an ensemble of SVM, kNN, and RF, the model was evaluated against 1,386 benign apps and 1,296 malapps. The study proved to have attained an accuracy of 98.4%, which was better than detection accuracy (95.8%) using only string features, while the accuracy obtained with only structural features was 90.68%.

Anomaly detection is a generic technique where any irregular traffic is flagged as a threat. Several studies [6, 43, 68] have attempted to provide secure IDS using ML algorithms. In this regard, an unsupervised DL technique called STL was used by Niyaz et al. [43], and it was based on SAE and SMR. By using NSL-KDD dataset, the comparison was made using 2-class, 5-class, and 23-class classification, and proved 2-class classification to be better than SMR. A multi-class ML-based classification using Mutual Information (MI) was proposed by Ambusaidi et al. [6]. For the linearly dependent variable, Mutual Information Feature Selection (MIFS) with Linear Correlation Coefficient (LLC) was used. For the non-linear dependent variable, the authors used FMIS+MI, made changes to the already existing MIFS algorithm [80] and showed their novelty. For the Linear model (Flexible Linear Correlation Coefficient based Feature Selection [FLCFS]), the study modified the existing LLC [80] and proposed a new model. An MI can cope with linear as well as non-linear dependents. However, its algorithm can cause redundancy to the classification. Ambusaidi et al. [6] chose ‘estimator’, which relied on estimating the entropies of the given data using average densities from each datum to its k-nearest neighbors. Another reason for this study was that the previous studies had not provided any steps as to how they chose $\beta$. The performance was compared using three different datasets of KDDCUP99, NSL-KDD, and Kyoto 2006+, while the metric performance indicators were Accuracy, DR, FPR, and F-measure. Maimo et al. [68] focused on 5G application for anomaly detection based on LSTM. Features extraction was made from network flows using weighted loss function, while feature reduction was made by using DBN and SAE models because of similar structure (where the prediction can be computed using matrix operations followed by the activation function) [68]. After implementing their model using CTU-13 botnet dataset, the authors claimed to have obtained a precision of up to 0.95.

Several studies using ML algorithms as a tool have claimed to reduce cyber-attacks effectively. However, Zhou et al. [122] based their proposal Deep Feature Embedding Learning (DFEL) on DL because a traditional ML algorithms took extra time to train data. The comparison of their proposal using the datasets of NSL-KDD and UNSW-NB15 confirmed the improvement in recall level of Gaussian Naive Bayes classifier from 80.74% to 98.79%, apart from the running time of SVM significantly reduced from 67.26 seconds to 6.3 seconds. In another similar study [78], the authors claimed that the existing ML algorithms were inefficient for IoT applications and therefore a much faster extreme-learning-machine (ELM) could be used instead [78]. Furthermore, they found that the existing security approaches for IoT were centralized and cloud-based, and they, in turn, inherited latency and high power consumption. The proposed IDS for IoT used fog computing for implementation in a distributed fashion in two steps. In the first step, attack detection at fog nodes used online sequential extreme learning machine (OS-ELM) to identify the attacks in the incoming traffic from the IoT virtual clusters. In the second step, these detected threats were summarized and analyzed at a cloud server. The results of the new algorithm showed better accuracy, FRP, and TPR after comparison with the existing NB, ANN, and standard ELM. Furthermore, the experimental results using the Azure cloud also confirmed that the fog-computing-based attack detection was faster than the cloud-computing based attack detection. However, the study did not compare the results with any existing ML/DL based algorithm used for fog-computing.
Table 8. Existing IoT security solutions using machine learning algorithms

| Ref. | Threat  | Type of Threat | IoT Use case | Algo used | Feature | Feature | Dataset | Accuracy |
|------|---------|----------------|--------------|-----------|---------|---------|---------|----------|
| [23] | DoS     | Flooding       | Fog          | LSTM      | -       | -       | I, A    | I (99.91), A (98.22) |
| [1]  | DoS     | Flooding       | Fog          | Softmax   | SAE     | -       | N       | 99.2     |
| [101] | DoS     | Flooding       | NIDS         | TAB       | MCA     | Norm.   | K       | normalized 99.95 |
| [102] | DoS     | Flooding       | CV           | EMD       | MCA     | PCA     | K, I    | K (99.95), I (90.12) |
| [74]  | Botnet  | Flooding       | IoT          | Adaboost  | CC      | -       | U, NB   | U (99.54) |
| [2]   | MiM     | Impersonation  | Healthcare   | LSTM RNN  | NG      | -       | P       | -        |
| [7]   | MiM     | Impersonation  | WiFi         | ANN       | D-FES   | -       | AWI     | 99.92    |
| [19]  | MiM     | Impersonation  | RF Comm      | ANN       | -       | -       | P       | 99.9     |
| [9]   | Malware | Code Injection | IoT          | DCN       | OpCodes | IG      | P       | 98.37    |
| [8]   | Malware | Malware        | Android      | -         | Static  | Manual  | P       | 98.9     |
|       | Malware | Malware        | Android      | NB, C4.5, kNN | Dynamic Analysis | NA | P | NG |
| [32]  | Malware | Malware        | Android      | ensemble + LR | Manual | Chi-Square | Ab, D | 98.18 |
| [110] | Malware | Malware        | Android      | ensemble | String + structural | Multi-sources | C | - |
| [68]  | Anomaly | Anomaly        | 5G           | LSTM      | Weighted Loss | ASD (DBN+SAE) | - | Ky | 2 - 88.39, 5 - 79.10 |
| [43]  | Anomaly | Anomaly        | NIDS         | Softmax   | -       | Ky      | K, N, Ky | K 99.95, I 90.12 |
| [6]   | Anomaly | Anomaly        | NIDS         | LSSVM     | MMIFS   | FMIS    | K, N, Ky | K 99.95, I 90.12 |
| [122] | Dataset | Multiple       | IoT          | DFEL      | -       | -       | N, U    | > 98.5 |
| [78]  | Dataset | Multiple       | Fog          | OS-ELM    | -       | -       | N       | 97.36    |
4.1.2 Privacy efforts. Several privacy-preserving ML algorithms have been proposed, as shown in Table 9. Similar to security, privacy is also compromised by a MiTM attack. In this regard, several studies have used ML algorithms to counter different types of MiTM attacks. For example, the study by Xiao et al. [113] used game theory - a kind of reinforcement learning, which compared the channel states of the data packets to detect spoofing attacks. The authentication process was formulated as a zero-sum authentication game consisting of the spoofers and the receivers. The threshold was determined by using Nash Equilibrium (NE), implemented over universal software radio peripherals (USPRs), and the performance was then verified via field tests in typical indoor environments. As an improvement to their work, Xiao et al. [114] applied logistic regression to evaluate the channel model information collected from multiple access points to detect spoofing more accurately. A comparison was made using distributed Frank-Wolfe (dFW)-based and incremental aggregated gradient (IAG)-based authentication to reduce overall communication overhead. IAG-based PHY-layer authentication reduced communication overhead and increased detection accuracy. The results showed improved FAR, DR, and computation costs by using a real-time dataset. In addition to authentication issues, Aksu et al. [4] raised an argument concerning the wearable device, for which the previous schemes only focused on user authentication. However, the device being used should also be authenticated. Such devices could act as MiTMx, which might have similar user authentication details. However, at the background, it might leak all the information to the attacker. Wearables could only connect to the more powerful base device via Bluetooth with authentication and encryption. Since the device name and encryption keys could be compromised easily, it was therefore much secure to use hardware-based fingerprinting [4]. The proposed framework in [4] utilized an inter-packet timing-based timing analysis method based on the Bluetooth classic protocol packets. There were four steps in this framework. The first step captured Bluetooth classic
packets. The second step extracted the features. In the third step, using probability distributions, the fingerprints were generated. Moreover, as a final step, the stored fingerprints in step three were compared with any new incoming data from wearable devices, to identify any unknown wearable device. By selecting the best algorithm out of twenty from the training results, the study claimed to achieve an accuracy of 98.5%.

Data plays a crucial role in training an ML model. For example, we can use patients’ historical data to make a predictive decision for any new patient. However, patients are reluctant to share their data due to obvious privacy concerns. The studies, as shown in [45, 65, 123], have worked towards solving these issues. In [123], the researchers proposed a new framework called eDiag, which used non-linear kernel SVM to successfully classify medical information, while preserving user data and service provider’s model privacy. Previous studies had used homomorphic encryption techniques, which, according to the study, were not appropriate for online medical prediagnosis. Using their framework, Zhu et al. [123] claimed to have achieved a classification accuracy of 94% without compromising privacy. Similarly, the authors in [45] classified the privacy issues as learning-privacy problem and model-privacy problem. The original data need to be protected since they contained sensitive user information which is related to learning-privacy, while the privacy of the model results as well as testing data are related to model-privacy.

Jia et al. [45] argued that the previous work used either gradient-values instead of real-data, or they assumed that learning model was private, but the learned model was publicly known, or they used complicated encryption procedures. In comparison to all of these studies, Jia et al. [45] proposed a uniform Oblivious Evaluation of Multivariate Polynomial (OMPE) model, which did not contain complicated encryption procedures. Their results proved that the classification data and learned models were protected from several privacy attacks. The research in [45] focused on model-privacy issues. However, the learning-privacy problem was not discussed. This issue was solved by Ma et al. [65], who argued that encrypting any user-data by the public key was a widely used privacy-preserving technique but at the cost of key management. To preserve the data privacy, Ma et al. [65] proposed a cloud-based DL model that worked with multiple keys to attaining privacy of the user data called Privacy-preserving DL Multiple-keys (PDLM). In their proposed model, a service provider (SP) sent encrypted user data to the cloud which performs training of the data without knowing the real data. Their evaluation of the PDLM showed that PDLM had successfully preserved privacy with lower efficiency as compared to the conventional non-privacy-preserving mechanism.

To improve ML algorithms privacy, Sun et al. [99] proposed an improved version of fully homomorphic encryption that reduced the size and noise of the multiplicative cyphertext by using the re-linearization technique. In their scheme, private hyperplane decision-based classification, private Naive Bayes classification, and private decision tree’s comparison were also implemented. In a similar paper, the same authors successfully reduced the user-server iterations to half, without compromising privacy.

Social media platforms like twitter and facebook have enriched people’s lives at the cost of privacy issues. Several companies used blacklisting techniques to filter benign traffic. However, a survey showed that 90% of the people would fall prey to these attacks before they were blacklisted. To prevent these attacks efficiently, ML algorithms were used; however, these algorithms were inefficient in real-time due to their slower learning rate. In a study, Feng et al. [31] proposed a multistage detection framework using DL, where an initial detection occurred at a mobile terminal whose results were then forwarded to the cloud server for further calculation. By using CNN as a classification algorithm, the authors claimed to achieve approximately 91% utilizing the Sino Weibo dataset. Similarly, the lack of privacy protection mechanism in a VANET environment was raised by Zhang et al. [119]. In VANET, Vehicle nodes tend to learn collaboratively, raising privacy
Table 9. Existing IoT privacy solutions using machine learning algorithms

| Ref. | Threat     | ToA            | Use Case       | Algo               | Dataset       | Accuracy       |
|------|------------|----------------|----------------|--------------------|---------------|----------------|
| [113]| MiTM       | Spoof detection| WSN            | QL, DQ             | Private       | NG             |
| [114]| MiTM       | Spoof detection| MIMO Landmark  | Softmax            | Private       | NG             |
| [4]  | MiTM       | Authentication | Wearable devices | best of 20       | Private       | Precision 98.5%|
| [65] | Data Privacy| Data Leakage   | Cloud          | SGD                | -             | accuracy loss 5%|
| [119]| Data Privacy| Inference attack| VANET         | LR                 | NSL-KDD       | -              |
| [45] | Data Privacy| Multiple       | Distributed Systems | OMPE              | realworld     | data classification |
| [123]| Data Privacy| Multiple       | Healthcare      | SVM                | realworld     | 94%            |
| [99] | Data Privacy| Multiple       | General         | HBD, NB, DT       | -             | -              |
| [31] | Anomaly    | Spam           | MSN            | CNN                | Sino Weibo    | 91.34%         |

concerns, where a malicious node can obtain sensitive data by inferring from the observed data. A single node has limited computational and memory resources. The solution was presented by using collaborative IDS with distributed ML algorithms and resolving the privacy issues by proposing the concepts of dynamic differential privacy to protect the privacy of a training dataset.

4.2 Existing solutions using Blockchain Technology

Blockchain (BC) is a secure mesh network [11], that is fault-tolerant, transparent, verifiable, and audit-able [20]. The frequently used keywords to describe BC benefits are decentralized, P2P, transparent, trust-less, immutable. These attributes make a BC more reliable than an untrusted central client-server model. The smart contract is a computer protocol on BC which guarantees the execution of a planned event [18]. According to Restuccia et al. [84], the blockchain guarantees data integrity and validity, making it a suitable solution for protection against data tampering in IoT devices.

4.2.1 Security efforts. Several BC-based solutions for supply-chain, identity management, access management, and IoT were proposed [53]. However, the existing solutions do not respect the time delay and cannot be applied to the resource-constrained IoT devices [66]. Machado et al. [66] offered data integrity for Cyber-Physical Systems (CPS) by splitting their BC architecture into three levels: IoT, Fog, and Cloud. At the first level, the IoT devices in the same domain created trust in each other using Trustful Space-Time Protocol (TSTP), which is based on Proof-of-Trust (PoT). At the Fog level, Proof-of-Luck (PoL) was used to create fault-tolerant IoT data which produces a cryptographic digest for a data audit. The data generated from the first level was hashed using SHA-256 and saved temporarily. After the acknowledgment and consensus were reached, the data was permanently stored at the third level of cloud, which is a public ledger. Other than data integrity, the study also offered key management using time synchronization and the location of the node. HECOPS was used to estimate the node’s location via multi-lateration, and TSTP provided clock synchronization. The paper proposed to used multiple consensuses, such as PoT and PoL, but it did not cater to any user privacy issue. Another paper [61] provided data integrity with the idea of securing data collected from the drone using public BC. DroneChain presented had four modules; drones, control system, cloud server, and a BC network. Drones were controlled by the control system, and the data was encrypted and stored using the cloud server on a decentralized BC. The resultant system was trusted and accountable, offered instant data integrity, and had a resilient backend. However, the study used PoW, which was not the best choice for a real-time IoT application like drones. In addition, the work did not offer data provenance and user/data security.

DoS attacks are one of the frequently executing attacks due to their comparatively straightforward implementation and the ever-growing number of insecure digital devices. Due to cheap IoT
technologies, hackers can easily control multiple IoT devices to launch an attack. According to [106], the SDN top layer is prone to brute force attacks. Since SDN is controlled by software, it can be targeted by injecting malicious applications, and also gives rise to the DoS/DDoS attacks. The earlier methods to prevent DDoS are not compatible with a light-weight multi-standard IoT environment. Other than that, SDN can suffer flooding attacks, saturation attacks, and MiM attacks due to lack of authentication in the plain-text TCP channel. Tselios et al. [106] argued that BC offered a better solution to protect IoT devices from security attacks and enforced trust between multi-vendor devices, as it was decentralized, fault-tolerant, and of tamper-proof. These valuable BC properties make it prone to data tampering and flooding attacks. However, all of the solutions mentioned above were theoretical ideas as no practical implementation was done. In another paper, Sharma et al. [90] improved the security vulnerability in SDN by proposing a distributed SDN architecture for IoT using BC called DistBlockNet. The BC was used to verify, validate, and download the latest flow rule table for the IoT forwarding devices. The proposed DistBlockNet model was compared with the existing solutions, and the results were better in terms of real-time security threat detections and overhead usage.

In another study, the researchers highlighted a MiTM security gap in a smart-grid, where any malicious actor could modify user data sent over the internet [34]. Secondly, the customers could not audit their costly utility bills, because the current smart-grid was unpredictable, and it did not provide any early warnings to the customer indicating higher energy usage. To avoid the above issues, this study proposed to use cryptographic data transmission using public and private keys for the user ID as well as the smart contract, which was placed on a BC. This technique ensured immutable, secure, and transparent smart-grid system. However, PoW could be extremely expensive and resource exhausting.

The study in [41] argued that the existing logistics systems were neither transparent nor credible to trace. The existing systems were centralized, relied on multiple TTPs, and focused on a single transporter. Hasan et al. [41] proposed a proof of delivery system using BC technique. In their transporter system, the nodes were seller, buyer, courier services, arbitrator and Smart Contract Attestation Authority (SCAA). The initial agreement was a smart contract that was placed on Inter-Planary File System (IPFS) and was executed once all the parties agree. The item was transported between several transporters as per the smart contract (maximum three in this paper), which was created every time for the next transporter. Finally, once the buyer is verified and collected the item, the payment is released to the seller. In the case of any rejection (i.e., transaction failure), the arbitrator takes over, settles the dispute and redistribute the amount based on the negotiated agreement. This proposed physical-asset-delivery system has inherent BC security against MiTM and DoS attacks. However, the authors have not paid any particular attention to user ID management and data privacy. The study by Gupta et al. [40] was a simulation done in OMENT++ on one application scenario where the authors claimed to have tackled Sybil attacks as well as the replay attacks in an IoT network. First of all, they introduced a new layered architecture, which had two more layers in the underlying IoT architecture. They explained their algorithm, idea, and work by comparison in terms of metrics of Transactions added to the BC per second (Ftx), Blocks added to the BC per second (Fblk), and Memory space utilized (Mmempool).

IDS is one of the widely used monitoring devices to detect anomaly traffic behavior. In a study by Golomb et al. [37], the authors argued that the current anomaly IDS were not efficient since the training phase considered only benign traffic. An adversary could exploit this vulnerability by injecting malicious data, which might be regarded as benign. Secondly, the trained model might not be as efficient, since it might be missing some IoT device traffic, which was only event-driven by, for example, a fire alarm. Both of the issues were solved by using a Collaborative IoT Anomaly (CIoTA) Detection using BC technique, where all IoT devices of the same type were trained simultaneously.
Since a large number of IoT devices were being trained based on their local data traffic, the chances of an adversarial attack were minimum. Each device would generate a locally trained model which would be collaboratively merged into a globally trained model by using BC technique. The study successfully implemented CIoTA and proved its benefits for eliminating the adversarial attacks. However, the separate block generated for each IoT model would increase the amount of data.

Along with the research on frequently researched security threats such as Data integrity, MiTM, and DoS, several studies have focused on providing solutions to multiple attacks. Sharma et al. in [89] presented an affordable, secure, and always accessible BC technique for a distributed cloud architecture. The combination of SDN and BC implemented the security of the fog nodes. The study brought the resource extensive tasks closer to the edge of an IoT network, which not only ensured better security but also improved end-to-end transmission delay. The authors further claimed that the model was adaptive based on the encountered threats and attacks, and reduced administrative workload. The main focus of this paper was to provide an architecture based on BC-cloud in fog computing, which was scalable, secure, resilient, and fast. The comparison was made in terms of throughput, response time, and false alarm rate. However, there was no consideration to the data privacy, user ID management, or the key management. Similarly, Sharma et al. in [92] claimed that the existing Distributed Mobile Management (DMM) lacked robustness against the security threats due to its centralized architecture. Their proposed scheme based on the BC showed improved latency, delay, and energy consumption, without affecting the existing network layout. However, the study used PoW consensus, which is energy-hungry and offered no user privacy.

All of the above solutions are mentioned in Table 10, where most of the researchers have focused on using PoW as a consensus algorithm, which is not suitable for a real-time IoT application. Moreover, most of them have not considered user anonymity and data integrity.

**Table 10. Existing IoT security solutions using blockchain techniques**

| Ref. | Threat | Use Case | BC used | BC type | Consensus | Security* | Weakness |
|------|--------|----------|---------|---------|-----------|-----------|----------|
| [66] | Data Integrity | Fog-Cloud | Ethereum | Public | PoW + PoL | D/K | No user security. |
| [61] | Data Integrity | Drone | - | Public | PoW | D/K | Slow BC + insecure |
| [106] | DoS | SDN | NG | Public | None | None | no U/D/K |
| [90] | DoS | SDN | Bitcoin | Public | PoW | None | Lack of data integrity & user security |
| [34] | MiTM | SmartGrid | NG | Private | PoW | U/D/K | Typical bitcoin architecture |
| [41] | MiTM | logistics | Ethereum | Private | PoW | K | No user/data security. Overall less secure |
| [40] | MiTM | IoT | Bitcoin | Public | Private | K | Simulation done for basic security |
| [37] | Anomaly | Network | Private | Public | Private | D/K | Block per IoT model will increase the data. |
| [89] | Multiple | Fog-SDN | Ethereum | Public | None | None | no user or data security is offered |
| [92] | Multiple | 5G | Multiple | Both | Multiple | none | PoW is costly, no U/D/K |

4.2.2 *Privacy efforts.* Privacy is a complicated issue in a BC that can be accomplished, but at the cost of throughput and speed [20]. A hacker can identify the patterns of a permissionless BC since all of the transactions happen in public and make an informed decision about the source. BC-based privacy-preserving was proposed by several researchers to solve this issue [3, 29, 39, 47, 58, 64, 82, 108, 121]. Wang et al. proposed a BC-based model, tackling the MiTM attack issues in a crowdsensing application [108]. The user privacy was implemented by using node cooperation method, in which the server released the sensing task as well as its prize, which was pre-paid on the BC. The users would perform the sensing task and upload the sensing data, and finally, the user was paid as per their achievements. To achieve user-data privacy, the authors proposed k-anonymity, in which the sensing task was not given to an individual, but a group and the sensed data gathered was also in the form of a group, which preserved privacy of a single-user. The announcement VANET is something in which the users (nodes) shared some information that might benefit other users in the
network. According to the researchers of CreditCoin [58], the current VANET system had a lack of privacy as well as motivation for the users to share any data. CreditCoin was proposed that offered decentralization, trust, and motivation by paying the user their incentives. The shared information was immutable, so the source did not fake any news either, benefiting the whole VANET community from it. For example, the information might be "a traffic accident on ABC road going towards XYZ". Another VANET application was proposed by Lu et al. in [64], where the authors added privacy to the users in the existing bitcoin platform using the lexicographic Merkle tree. Furthermore, the forgery was controlled by adding a reputation weight to every vehicle in the network. However, the study used PoW as their consensus protocol, which is very costly and can create traffic bottlenecks in a resource constraint VANET application.

First, of its nature, Zhou et al. [121] claimed to design the BC-based IoT system where the servers helped users to process encrypted data without learning from the data. Homomorphic encryption was used to secure the data in a private BC using PBFT consensus. The authors in [82] argued that although the BCs were immutable and tamper-proof, once a block was executed, they did not cater confidentiality and privacy of the data as anyone could see the plain-text. When such a BC was integrated with IoT, it was more vulnerable due to a massive influx of data. Rahulamathavan et al. focused on these issues by proposing a privacy-preserving BC architecture for IoT applications based on the Attribute-based Encryption (ABE) [82]. The previous studies offered the solution by using the symmetric encryption like AES, which meant that the key must be shared with the data to enable the miners of the BC to verify the content and update the BC. However, such a technique could not guarantee privacy. ABE used single encryption to keep data private and safe. In a scenario of a hospital, the main server could encrypt data before transmitting the attributes, such as DOCTOR or NURSE, which could only be read by the concerned node by using the same attributes and decrypting them. The BC architecture could secure data manipulation since multiple nodes verified a single transaction. After the approval, the data was stored and could not be tampered. Lastly, there was no central control, making all of the transactions transparent and fair. However, the cluster head could read the data, which might be exploited by an attack.

Fan et al. working in the 5G network application argued that the work on access control of an encrypted data still needed to be explored [29]. Despite several advantages of ABE, if a user wanted to change his policy, the attribute revocation and re-encryption took much time. Additionally, the owners did not control their public data, and the trust was delegated to the third parties. Centralized systems were fault-prone, and could cause traffic choking. Fan et al. used BC to solve these issues, by using encrypted cloud storage for the provision of privacy-preserving and data-sharing system, which was tamper-resistant, fully controlled by the user, and always accessible to anyone on request [29]. However, their proposal had several drawbacks; for example, the miners could share the information without user consent. Moreover, the BC proposed is public, which mean anyone could access it.

Aitzhan et al. [3] addressed the issues of transaction security and privacy by using multi-signatures. Since the traditional systems were insecure, unreliable, and publicly accessible, the messages were sent in an encrypted form that offered privacy and security in communication. User anonymity was ensured by using the public key and private key. Similarly, another concept of multi-signatures was mentioned by Guo et al. [39]. The authors found that the current Electronic Health Record (EHR) system was centralized with no user privacy or control over it. Health records are critical documents as they have a personal medical history. The user should be in control of them, but they should be unforgeable as well. In previous studies, Attribute-Based Signatures (ABS) enabled trust between the two parties; however, it was unreliable and restricted to a single signature. Encashing the ABS advantages, Guo et al. presented an ABS with multiple access (MA-ABS), which guaranteed privacy with access control to the user, and confidence of real information to the
verifier [39]. Moreover, using BC for maintenance of data reinforced immutability, unforgeability, and decentralization. Privacy-preserving was achieved by using MA-ABS and collusion attacks were avoided by using pseudorandom function seed. The study also proposed Key management by using KeyGen.

In a similar attempt, [47] offered a new consortium BC called PETCON, that was based on the bitcoin platform using PoW for the PHEV to trade the surplus electricity between them. The existing P2P was a single point of failure, and it was expensive and untrustworthy. Kang et al. [48] improved upon the privacy of a vehicular data in the existing P2P data sharing networks. Due to the resource constraints in a vehicular system, the data was forwarded to the edge computers for powerful computation. The data shared was vulnerable, due to which, the researchers in this study used consortium BC, where only the selected nodes could perform the audit and verification. They also introduced the use of smart-contracts, which ensured user-authenticity and secure data-sharing, and improved data-credibility. The consortium model reserved the energy as it selected a lesser number of nodes for data maintenance. Vehicle-ID authentication was done by digital signatures using public/private keys, while *Elliptic curve digital signature algorithm* provided key-management. The authors also touched upon data privacy management by storing the raw data using the proof-of-storage.

### Table 11. Existing IoT privacy solutions using blockchain techniques

| Ref. | Threat | Use Case | BC used | BC type | Consensus | Privacy* | Weakness |
|------|--------|----------|---------|---------|-----------|----------|----------|
| [108] | MiTM | Crowdsensing | Bitcoin | Private | PoW | U/D | Prone to collusion + detail missing |
| [58] | MiTM | Vanet | Private | Private | PoW | U/D/K | Poor key management |
| [64] | Data Privacy | VANET | Bitcoin | Private | PoW | U/D/K | PoW is slow & not ideal for real-time scenario. |
| [12] | Data Privacy | IoT | Ethereum | Private | PBFT | U/D | Block time not suitable for real-time IoT |
| [82] | Data Privacy | IoT | Bitcoin | Public | PoW | D/K | Unsuitable for realtime IoT as block time is 10 m. |
| [29] | Data Privacy | 5G | Private | Public | DPos | U/D/K | Miners can share data & store data, BC is public. |
| [3] | Data Privacy | Smartgrid | PriWatt | Public | PoC | U | No D/K + limited to SG |
| [39] | Data Privacy | Healthcare | Private | Public | NG | U/D/K | No BC model/consensus technique is mentioned. |
| [47] | Data Privacy | PHEV | PETCON | Consortium | PoW | K | No user privacy or data privacy |

* U: User privacy, D: Data privacy, K: Key management

### 4.3 Existing solutions using Machine Learning and Blockchain

In this section, we look at the existing security and privacy solutions for IoT with the integration of ML algorithms and BC techniques.

#### 4.3.1 Security Solutions

Agrawal et al. claimed to eliminate spoofing attacks with the combination of ML algorithms and BC techniques [94]. By securing the user-device communication, the user in a valid IoT-zone is continuously monitored, and the communication logs are saved on the BC. The records are immutable and can be verified for any suspicious activities. The existing user authentication techniques include one-time-password (OTP) or security questions, which are limited to single authentication. By using hyperledger as a BC platform, the authors resolved this issue by considering continuous security using IoT-zone identification, IoT-token generation, and token validation. However, the study considered IoT-hub as a center of communication, which voided the concept of decentralization. There was no user or data privacy in concern, and the dataset was too small for a DL model.

Gu et al. [38] mentioned that, due to its open-sourced nature, the Android-based systems were highly targeted by malware, trojans, and ransomware. The existing schemes can be classified as either static-based analysis or dynamic-based analysis, had certain drawbacks such as code obfuscation, high time cost, and encryption. The study proposed a new multi-feature detection model (MFM) of Android-based devices, where they utilized a fact-base of malicious codes by using
Consortium BC for Malware Detection and Evidence Extraction (CB-MDEE) in mobile devices. Compared with the previous algorithms, CD-MDEE achieved higher accuracy with lower processing time.

Table 12. Existing IoT security solutions using machine learning algorithms and blockchain techniques

| Ref. | Attacks | Use Case | Algo | Dataset | Metric | BC used | BC type | Consensus | Privacy* |
|------|---------|----------|------|---------|--------|---------|---------|-----------|----------|
| [94] | MiTM    | IoT      | VMM+ LST | Private | Accuracy | Hyperledger | Private | PBFT | K        |
| [38] | Malware | Android  | MFM  | Drebin | FPR, DR, Acc | Private | Consortium | -         | none     |

Table 13. Existing IoT privacy solutions using machine learning algorithms and blockchain techniques

| Ref. | Attacks | Use Case | Algo | Dataset | Metric | BC used | BC type | Consensus | Privacy* |
|------|---------|----------|------|---------|--------|---------|---------|-----------|----------|
| [70] | Data Leakage | General | CNN | Private | Accuracy | Ethereum | Private | PoS | D        |
| [95] | Data Privacy | Smart Cities | SVM | BCWD+HDD | Accuracy | NG | NG | PoW | U/D/K  |

4.3.2 Privacy Solutions. Many companies rely on big datasets to optimize their target audience and enhance their profits, but such data contain sensitive personal information, such as political preferences, which can be exploited by interested entities. It is, therefore, crucial to preserve the privacy of such users, and if required, compensate them for their contributions. Moreover, certain domains have an abundance of data, which can be beneficial for research and development, but the data cannot be shared with third parties. Furthermore, the same data can be manipulated and raise doubts on its integrity. To improve upon the above architecture, Mendis et al. [70] proposed fully autonomous individual contributors working in a decentralized fashion without disturbing the functionality and overall efficiency. Smart contracts incentivizing the computing contributors executed the peer-to-peer transactions. However, the architecture was based on the ethereum BC having a block time of 12 seconds, and hence it was not feasible for a real-time IoT application, for example, video streaming.

ML classifiers require datasets to train. These datasets are collected from different entities who are usually reluctant to share their data due to several privacy concerns such as data leakage, data integrity, and ownership. The users do not know how and when their data may be used. To preserve these privacy issues, Shen et al. [95] proposed a fusion of machine learning with blockchain. A privacy-preserving SVM based classifier was used to train the encrypted data collected from IoT users, while the BC platform provided data sharing among multiple data providers. However, the solution used encryption techniques to preserve privacy, which is not suitable for a resource constraint IoT device. The use of the BC platform is also not explained in detail.

5 RESEARCH CHALLENGES

5.1 Challenge to Machine Learning Algorithms in IoT
ML algorithms are utilized for analysis after being trained on a large number of dataset, to adapt to the desired output dynamically. These models may be used, for example, in navigating a robot or for speech recognition, where human expertise either does not exist or cannot be used. ML algorithms have also been utilized very efficiently to analyze threats against several cybersecurity domains. Although ML algorithms perform well in many areas, they have some limitations in the IoT environment:
Scalability and Complexity issues: In recent studies, several ML algorithms have effectively reduced the cyber attacks. However, ML algorithms are not an ideal pick for IoT applications due to its limitations. Diro et al. claimed that the traditional ML algorithms were limited in scalability, feature extraction, and accuracy [23]. Whereas, Moustafa et al. [74] argued that ML algorithms could not solve many problems, primarily when it was implemented in a complex resource-constrained IoT environment. Another work done by Abeshu et al. [1] proved that the traditional ML algorithms were less scalable and less accurate in a vast distributed network such as IoT. After comparing classical ML algorithms with DL methods, several studies learned that most of the DL techniques used pre-training for feature extraction. DL not only saved administrative time but also reduced feature dimensionality by reducing redundancy [43, 49, 60, 87, 116].

Latency issues: As a solution to the above issues, some authors, for example, Xiao et al. [114] proposed to use ensemble ML algorithms. The ensemble algorithm proved to be performing better than each ML algorithm individually, but it was computationally expensive. As an alternative to classical ML, most of the studies pointed out that DL is a better choice for IoT. In another study, the authors proposed Deep Feature Embedding Learning (DFEL) [122]. They utilized the DL-based model because the traditional ML algorithms increased training time in Big Data scenarios. Using the datasets of NSL-KDD and UNSW-NB15, they claimed to have improved in the recall of Gaussian Naive Bayes classifier from 80.74% to 98.79%. Moreover, their method significantly reduced the running time of SVM from 67.26 seconds to 6.3 seconds. The improvement in recall-rate and running time perfectly suit an IoT application.

Compatibility issues: Although the above solutions have performed better, we believe that these DL-based techniques are application-specific. In such cases, a model trained for solving one problem may not be able to perform well for another problem in the similar domain [42].

Vulnerability issues: One of the critical challenges to the ML/DL techniques in IoT is to secure themselves from any security or privacy attacks. These threats are highlighted in Fig. 6, which can be proven deadly. For example, in a healthcare application, where an ML algorithm is used to analyze the amount of insulin, a patient should be given. If an adversary is able to inject malicious code and alter the input to the ML algorithm, the amount of insulin may be increased and cause death to the patient.

In regard to the above issues, we believe that the ML algorithms for IoT need optimization for better scalability, higher speed, better compatibility, and improved security and privacy. We think that privacy-preserving ML algorithms, such as differential privacy and light-weight homomorphic encryption, should be explored to overcome the discussed challenges.

5.2 Challenges to Blockchain in IoT

Latency and speed issues: Although the BC technology was introduced a decade ago, its real benefits were realized only recently. In recent studies, many efforts have been made to utilize BC in several applications, such as logistics, food, smart grid, VANET, 5G, healthcare, and crowdsensing. However, the existing solutions do not respect the latency issues of BC, and cannot be applied to the resource-constrained IoT devices [24, 66]. The most widely used BC consensus is PoW, as depicted in Table 11. PoW is a slow (limited to seven transactions per second as compared to an average of two thousand transactions per second for the visa credit network) and requires a lot of energy [12, 18, 20].

Computation, processing, and data storage issues: There is a substantial cost of computation, power, and memory involved in maintaining a BC across a vast network of peers [12, 97]. According to the Song et al., in May 2018, the bitcoin ledger size had surpassed 196 GB. These limitations suggest poor scaling and transaction speed for an IoT device. Although
an alternative was to offload their computation tasks onto a central server - cloud, or a semi-decentralized server - fog, this, however, adds network latencies [85, 97].

- **Compatibility and Standardization issues**: Like any emerging technology, one of the BC challenges is its standardization for which the laws need to be reformed [75]. Cybersecurity is a difficult challenge, and it would be naive to think that we all will see a security and privacy standard that can eliminate all risks of cyber-attack against IoT devices anytime soon. Even so, a security standard can ensure that devices meet "reasonable" standards for security and privacy. There are a number of fundamental security and privacy capabilities that should be included in any IoT device.

- **Vulnerability issues**: Although the BC is non-repudiable, trustless, decentralized and of tamper-proof, a blockchain-based system is only as secure as the system’s access point. In a public BC-based system, anyone can access and view the data contents. While the use of private blockchain is one of the solutions to the above problem, it raises other issues like trusted third party, centralized-control and access-control legislations.

The IoT devices can generate a massive amount of data, which should be typically processed in real-time. Since the demand for IoT-based BC is different, there is much research going on to bring a new BC that is compatible with IoT. The most important limitations on BC, however, are ledger storage and transaction per second (TPS). Although in the latest BCs such as hyperledger fabric TPS is down to milliseconds, a lot still needs to be done for a BC to work smoothly in the IoT environment. Similarly, in the context of secure BC model of IoT, the security needs to be built-in, with validity checks, authentication, and data verification, and all the data needs to be privacy-preserved at all levels. We need a secure, safe, and privacy-preserved IoT framework.

6 CONCLUSION AND FUTURE WORK

In this paper, we have reviewed the latest threats to IoT and categorized them into security and privacy. Their effects, type of attack, the layer of impact and solutions have been briefly mentioned. We have then comprehensively presented the latest existing literature survey on IoT security and privacy using ML algorithms as well as BC technologies and highlighted their gaps. This paper has presented the current solutions to IoT security and privacy by utilizing ML algorithms, BC techniques, and the integration of both. To better understand the security and privacy issues in an ML, we have also attempted to present an ML threat model for IoT based on the previous studies. Finally, few research challenges to ML algorithms and BC techniques in IoT have been discussed.

The generation, storage, analysis, and communication of data are fundamental to the IoT ecosystem. A holistic approach is in demand, where a vulnerability-free system needs to be built, through measures such as adherence to best practices and continual testing. The system should be able to learn and adapt to the latest trends in threats (zero-day attacks) since malicious activities are dynamic. In this regard, ML/DL can be extremely beneficial in analyzing the traffic, while the BC can serve as a basis to keep a ledger of logs and communication in an IoT environment. Since this data is immutable, it can be used confidently in the court of law as a piece of evidence.

Although many studies have been conducted on IoT security and privacy, most of them have been focused on providing either security or privacy. We believe that for a system to be secure, both security and privacy are equally important. Moreover, the privacy of data is the most critical factor, which can only be valid when considered end-to-end. The current system lacks the integrity of datasets that are being used to train a model. Any adversary can tamper these datasets to obtain their desired results. Currently, the integration of ML algorithms with BC techniques to achieve IoT security and privacy is a relatively new area, which needs to be explored. In the future, we aim
to design and develop a privacy-preserving IoT framework, which will offer privacy-preserving data sharing as well as privacy-preserving data analysis

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