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Exploring lightweight machine learning models for personal internet of things (IOT) device security

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Abstract

The proliferation of Internet of Things (IoT) devices in personal and household environments has led to a significant increase in security vulnerabilities. These devices, due to their limited computational resources, often struggle to support conventional security solutions, making them prime targets for cyberattacks. This paper explores the potential of lightweight machine learning (ML) models to enhance the security of personal IoT devices. By leveraging the power of AI, lightweight models can offer real-time threat detection and anomaly identification without compromising the device's performance or requiring extensive computational resources. The paper investigates various ML techniques that are well-suited for IoT environments, such as decision trees, k-nearest neighbours (KNN), and support vector machines (SVM), focusing on their ability to detect intrusions, unauthorized access, and other malicious activities while maintaining efficiency. Additionally, the study highlights the trade-offs between model complexity, accuracy, and resource consumption, offering practical insights for deploying ML solutions in resource-constrained IoT systems. Key challenges, including data privacy, model generalization, and the adaptability of models to diverse IoT ecosystems, are addressed. Finally, the paper discusses future directions for the integration of more advanced lightweight models, such as federated learning and edge computing, which could further enhance security capabilities while ensuring minimal impact on IoT device performance. Through this review, the paper advocates for the adoption of lightweight ML models as a feasible and scalable solution to securing personal IoT devices in an increasingly connected world.

Keywords: IoT Security; Lightweight Machine Learning; Intrusion Detection; Anomaly Detection; Edge Computing; Federated Learning

1. Introduction

1.1. The Rise of Internet of Things (IoT) Devices in Personal and Home Settings

The Internet of Things (IoT) has become a transformative force in the modern world, particularly in personal and home settings. IoT refers to a network of interconnected devices that communicate and exchange data to improve functionality and automate everyday tasks. Examples of such devices include smart thermostats, security cameras, wearable health trackers, smart refrigerators, voice assistants, and lighting systems. These devices are designed to enhance convenience, efficiency, and the overall quality of life by offering users remote control, automation, and real-time data monitoring.

The global proliferation of IoT devices has been substantial in recent years, driven by advancements in connectivity, miniaturization of hardware, and the integration of AI. According to a 2023 report by the International Data Corporation

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(IDC), the number of connected IoT devices is expected to reach over 30 billion by 2025, with a significant proportion of these devices being used in residential settings (IDC, 2023). This rapid expansion is reshaping how people interact with their homes, healthcare, and daily routines. As IoT devices become ubiquitous in personal environments, they are increasingly embedded in critical aspects of daily life, making them essential to modern homes and personal security.

1.2. Increasing Vulnerability of IoT Devices to Security Threats

While IoT devices offer immense benefits, they also introduce significant security challenges. Their integration into home networks and reliance on continuous internet connectivity makes them attractive targets for cyberattacks. Unlike traditional computing devices, IoT devices often have limited processing power, storage, and security features, which makes them inherently more vulnerable to exploitation. Furthermore, many IoT devices lack robust encryption or authentication mechanisms, exposing them to risks such as unauthorized access, data breaches, and remote manipulation.

In a home setting, a compromised IoT device could serve as a gateway for attackers to gain unauthorized access to other connected devices or the home network itself. For instance, smart security cameras, doorbell systems, and voice assistants could be hacked to monitor private conversations, disable alarms, or gain access to home networks, potentially leading to identity theft, financial losses, or physical security breaches (Savaglio C et al., 2019). The problem is compounded by the fact that many IoT devices are designed to be installed and operated with minimal user intervention, leading to lax security practices such as default passwords and outdated firmware.

Moreover, the growing number of IoT devices presents a challenge in securing them all, as each device may have different security vulnerabilities, configurations, and manufacturer-specific flaws. This fragmentation further complicates the task of managing security across the entire network, leaving personal IoT ecosystems exposed to attack.

1.3. Exploring Lightweight Machine Learning (ML) Models for Securing Personal IoT Devices

As the number and complexity of IoT devices continue to increase, traditional security measures may no longer suffice to protect them from evolving threats. One promising solution to this problem is the use of lightweight ML models to enhance the security of personal IoT devices. ML algorithms, particularly anomaly detection and pattern recognition, can play a crucial role in identifying and mitigating security threats by continuously monitoring device behaviour and network traffic.

The advantage of leveraging ML for IoT security lies in its ability to detect new and unknown attacks without relying solely on predefined signatures or rules. This approach allows for the dynamic detection of suspicious activities that deviate from normal device behaviour, making it highly effective in identifying zero-day attacks or novel threats that traditional security systems might miss (Shao et al., 2021). ML models can also be designed to run efficiently on resource-constrained IoT devices, ensuring that security mechanisms do not hinder device performance or battery life.

Lightweight ML models, such as decision trees, support vector machines (SVMs), or lightweight neural networks, offer a balance between performance and resource utilization. These models can be trained locally on IoT devices or at the network's edge, allowing for real-time threat detection and response. The use of lightweight models ensures that devices with limited processing power can still participate in securing the network without sacrificing their core functionality (Punithavathi P et al., 2019).

The ability to deploy ML models directly on IoT devices is an exciting development in the realm of cybersecurity, as it enables decentralized security measures. By continuously learning from patterns of normal behaviour, ML models can adapt to new threats, improving their detection capabilities over time. Furthermore, these models can be tailored to specific types of devices and use cases, ensuring more accurate and effective protection for each individual device in the network. With this foundation in place, the unique constraints and challenges in securing IoT devices, particularly in terms of resource limitations, scalability, and the complexity of maintaining a secure ecosystem across a vast array of devices shall further be discussed.

2. Security challenges in personal IoT devices

2.1. Characteristics of IoT Devices

IoT devices are rapidly proliferating across various industries and homes, bringing significant benefits in terms of efficiency, convenience, and automation. However, these devices' characteristics, including their heterogeneity,

resource constraints, and connectivity challenges, introduce substantial security and management issues, especially in large-scale environments.

2.1.1. Device Heterogeneity

One of the primary characteristics of IoT devices is their heterogeneity, as these devices vary greatly in terms of their functionalities, communication protocols, and the technology they utilize. IoT systems range from simple devices like temperature sensors to complex systems such as smart cameras, home appliances, and medical devices. This diversity leads to integration challenges in IoT networks, as devices with different hardware, software, and operating systems must coexist and communicate effectively (Savaglio C et al., 2019). For instance, while smart thermostats may use Zigbee for low-power communication, security cameras might rely on Wi-Fi or Ethernet for high-bandwidth data transfer (Li et al., 2020).

The vast differences in device capabilities can create significant gaps in implementing uniform security protocols across the IoT ecosystem. As IoT devices become more interconnected, vulnerabilities in any one device—due to outdated software or weak security measures—could potentially compromise the security of the entire network (Savaglio C et al., 2019). Inadequate standardization also complicates the deployment of robust security measures, as each type of device requires customized protection strategies (Punithavathi P et al., 2019).

2.1.2. Resource Constraints

Many IoT devices are designed with limited computational resources to reduce costs and enhance energy efficiency, often operating with minimal power and memory. These constraints severely limit the ability to deploy sophisticated security mechanisms, such as advanced encryption, deep learning models, and other computationally intensive tasks (Shao et al., 2021). The lack of processing power on devices like wearable health monitors or smart appliances means that they cannot perform resource-heavy tasks locally. This necessitates offloading more complex data processing to cloud servers or edge devices, raising concerns about data privacy and the security of the transmission channels (Ogbodo EU et al., 2022).

Moreover, the inability to deploy robust security protocols directly on resource-constrained IoT devices makes them more susceptible to attacks. For example, attacks such as Distributed Denial of Service (DDoS) can overwhelm devices that are unable to detect malicious traffic patterns due to their limited computing capabilities (Singh et al., 2021). While lightweight ML models and simple security algorithms are often used, these solutions are not as effective at detecting complex attacks, thus posing a significant challenge in securing IoT systems (Shao et al., 2021).

2.1.3. Connectivity Issues

Connectivity is another major concern for IoT devices, as these devices typically rely on wireless communication protocols like Wi-Fi, Bluetooth, Zigbee, and cellular networks. These connections are prone to interference, congestion, and signal degradation, which can disrupt the devices' performance and increase the risk of security breaches (Xie et al., 2021). Poor connectivity can lead to failures in device authentication, data loss, or delays in applying security updates, leaving devices vulnerable to attacks (Punithavathi P et al., 2019).

Furthermore, the scalability of IoT networks often exacerbates connectivity issues. As more devices are added, network congestion can increase, and the system's ability to maintain stable communication between devices can become strained (Zhuang et al., 2020). In large-scale IoT environments, such as smart cities or industrial IoT, ensuring seamless and secure connectivity becomes increasingly difficult. Devices with poor connectivity may fail to communicate with central systems or other devices, resulting in inefficient operations and potential security vulnerabilities (Ogbodo EU et al., 2022).

The figure illustrates a typical IoT network in a home setting, showing the interconnected devices and communication protocols used. Devices like smart thermostats, cameras, and light bulbs communicate through a central home gateway, which connects to cloud storage or edge computing servers. The variety of devices and communication standards underscores the complexity in managing IoT systems securely. Therefore, the characteristics of IoT devices, such as their heterogeneity, limited resources, and connectivity issues, create significant challenges in managing and securing IoT networks. These challenges require innovative approaches, such as lightweight ML models, to mitigate vulnerabilities. As IoT devices continue to proliferate, addressing these issues will be critical to ensuring the security and functionality of personal and home IoT systems.

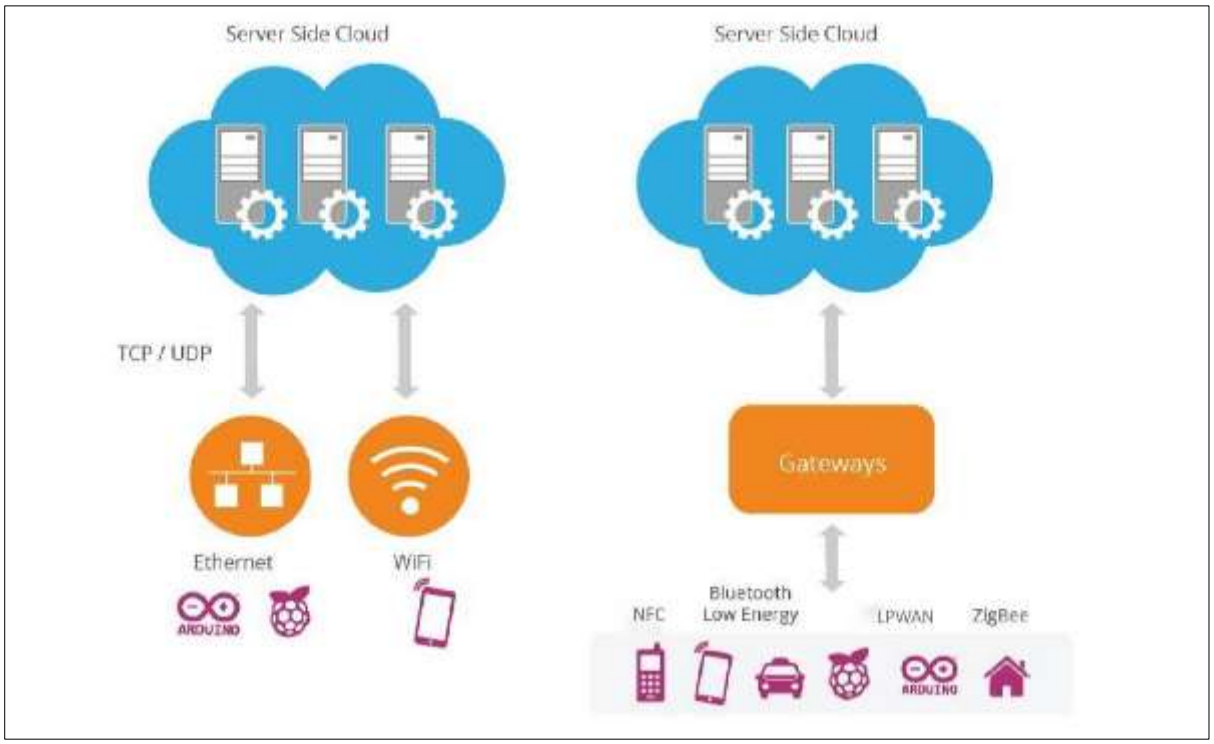

Figure 1 Diagram Depicting Typical IoT Devices and Their Interconnected Network (Ogbodo EU et al., 2022).

2.2. Common Security Threats in IoT Devices

The proliferation of IoT devices in personal and home environments has introduced new vulnerabilities, as these devices are often interconnected and constantly transmitting data Falliere et al. (2011). The diversity of devices, the limited security capabilities of many, and the vast number of entry points into the network make them attractive targets for cyberattacks. This section explores the various types of security threats that affect IoT devices, along with real-life examples of breaches involving personal IoT devices.

- Types of Attacks
- **Distributed Denial of Service (DDoS) Attacks:** DDoS attacks are one of the most common and impactful threats to IoT networks. In these attacks, malicious actors use a large number of compromised IoT devices (botnets) to flood a target system with traffic, overwhelming it and causing service disruptions. These attacks are particularly effective against IoT networks due to the typically low security and computing capabilities of IoT devices, which can be hijacked and used to generate massive amounts of traffic. According to Antonakakis et al. (2017), DDoS attacks often involve a botnet of IoT devices that exploit weak authentication protocols or vulnerable device configurations. The *Mirai botnet* attack in 2016, which involved thousands of IoT devices, demonstrated the effectiveness of these attacks. The botnet exploited weak default credentials and unsecured devices, which led to major service disruptions, including the temporary shutdown of services like Dyn, which provides infrastructure for major websites such as Twitter, Reddit, and Spotify (Moore et al., 2017).
- **Data Theft:** IoT devices often collect, store, and transmit sensitive personal data, including health information, location data, and user behaviour patterns. If compromised, attackers can steal this data, leading to privacy breaches and identity theft. The unprotected transmission of data between devices and cloud servers increases the risk of interception by cybercriminals. Furthermore, the lack of end-to-end encryption and weak authentication mechanisms in many IoT devices makes it easier for attackers to access valuable information. The potential for data theft was highlighted by He et al. (2018), who discussed how IoT medical devices are vulnerable to data breaches. In 2017, researchers discovered that attackers could steal sensitive health information from insulin pumps and pacemakers, which were connected to the Internet. Similarly, IoT-connected home security devices have been targeted, allowing cybercriminals to steal private user data (Symantec, 2019).
- **Ransomware:** Ransomware attacks are increasingly affecting IoT devices, with attackers taking control of devices and demanding ransom for restoring access. In a typical ransomware attack, the malware encrypts the files on the compromised device or locks users out, rendering it unusable until a ransom is paid. For IoT devices,

this can mean anything from locking users out of smart home appliances to preventing the use of critical devices in healthcare, manufacturing, or other sectors.

- Gajek et al. (2018) noted that ransomware is particularly dangerous for IoT devices due to their pervasive use in personal, industrial, and medical settings. In one instance, IoT-connected cameras were targeted by ransomware in 2018, locking users out of their devices and demanding payment for recovery. Such attacks highlight the growing risk posed by ransomware to IoT networks, which often lack adequate security measures (Gajek et al., 2018).
- **Man-in-the-Middle (MitM) Attacks:** MitM attacks involve intercepting and potentially altering communications between IoT devices. As IoT devices often communicate wirelessly, it is easier for attackers to intercept these communications using various techniques, such as signal jamming or spoofing. In a MitM attack, the attacker can listen in on or manipulate the data being transmitted between the device and the network, leading to data theft, unauthorized access, or system malfunctions. Fernandes et al. (2019) explored how MitM vulnerabilities were exploited in smart home devices such as security cameras and smart locks. Attackers were able to intercept data communications between the devices and the cloud server, capturing sensitive information like passwords or device commands. This type of attack emphasizes the importance of secure communication protocols and encryption in protecting IoT networks.
- **Physical Tampering and Unauthorized Access:** Physical tampering is another major threat, where attackers gain physical access to a device to either compromise it or steal sensitive information stored on it. This threat is more prevalent in devices used in environments with less physical security, such as smart meters, industrial IoT devices, or remote sensors in agriculture. Attackers may bypass authentication and physical security mechanisms to gain access to the network Falliere et al. (2011).
- According to Falliere et al. (2011), the *Stuxnet* attack, though not directly involving personal IoT devices, demonstrated the potential for physical tampering and remote attacks on critical infrastructure. This example serves as a warning for personal IoT devices, which could be similarly vulnerable to such attacks, especially when deployed in less secure environments like homes.
- **Botnet Infections and Malware:** IoT devices are often used as part of botnet attacks. Once compromised, these devices can be controlled remotely by cybercriminals to perform malicious activities, such as launching DDoS attacks, spreading malware, or conducting data theft. The Mirai botnet mentioned earlier is an example of how botnets are created using IoT devices. These infected devices are typically unaware of the breach and continue operating normally, making detection difficult According to Wang et al. (2017).
- According to Wang et al. (2017), botnet infections are a major risk for IoT devices, as they often have hardcoded passwords and weak security features. Once compromised, these devices can serve as gateways to larger networks, providing attackers with access to sensitive systems and information.
- **Spoofing and Device Impersonation:**Spoofing involves pretending to be a legitimate IoT device or service in order to gain unauthorized access to the network or data. In spoofing attacks, attackers mimic the identity of authorized devices and gain access to sensitive data or control systems. Device impersonation attacks are particularly concerning in the context of smart homes and industrial systems, where attackers can impersonate sensors or control systems to cause disruptions or steal data.

Symantec (2019) identified several instances where hackers successfully spoofed IoT devices, gaining unauthorized access to smart home systems. In these attacks, the hackers impersonated the identities of connected smart devices, such as security cameras, to manipulate user data or gain control of systems. This type of device impersonation exploits weak authentication mechanisms in IoT ecosystems and presents a growing security challenge. Understanding the variety of threats and vulnerabilities that IoT devices face highlights the need for robust solutions to secure these devices. Lightweight ML models present an efficient approach to detecting and mitigating these threats, offering real-time security with minimal computational overhead. The next section delves into how ML can be utilized to address the security challenges faced by IoT systems.

3. ML approaches for IOT security

3.1. Overview of ML Techniques Used in Cybersecurity

ML has become an indispensable tool in modern cybersecurity, offering a more adaptive, accurate, and scalable way to detect and mitigate security threats. ML techniques, ranging from supervised learning to reinforcement learning, are leveraged to address a wide array of challenges in protecting networks, devices, and data. These techniques allow systems to learn from data, adapt to new threats, and continuously improve their defense mechanisms. This section provides an overview of key ML techniques used in cybersecurity, with a focus on their applications and the comparison between traditional and lightweight models.

3.1.1. Supervised Learning

Supervised learning is one of the most commonly used ML techniques in cybersecurity. In supervised learning, a model is trained on a labelled dataset, where each input data point is associated with a corresponding output or label. The model's task is to learn the mapping between the input and output so that it can predict the output for new, unseen data points. In the context of cybersecurity, supervised learning is often used for tasks like spam detection, intrusion detection, and malware classification.

One of the main strengths of supervised learning is its high accuracy when enough labelled data is available. For instance, intrusion detection systems (IDS) can use supervised learning algorithms like decision trees, SVM, or deep neural networks to classify network traffic as benign or malicious based on historical data (Srinivasan et al., 2019). However, the need for large labelled datasets can be a challenge, especially in domains where collecting labelled data is expensive or time-consuming (Hodge & Austin, 2004).

3.1.2. Unsupervised Learning

Unlike supervised learning, unsupervised learning does not rely on labelled data. Instead, the algorithm seeks to identify patterns, correlations, or structures within the data. Unsupervised learning is particularly useful for detecting unknown threats, such as novel malware or zero-day attacks, because it does not require prior knowledge about specific attack signatures.

Common unsupervised learning techniques include clustering algorithms like k-means and density-based spatial clustering of applications with noise (DBSCAN), as well as dimensionality reduction techniques like principal component analysis (PCA). These methods are employed in anomaly detection, where the system learns the normal behaviour of a network or device and flags deviations as potential security threats (Chandola et al., 2009).

In cybersecurity, unsupervised learning can help detect emerging threats and anomalous behaviour without the need for predefined labels or attack patterns. However, one of the challenges with unsupervised learning is the difficulty in interpreting results and distinguishing between benign anomalies and actual threats (Xia et al., 2015).

3.1.3. Reinforcement Learning

Reinforcement learning (RL) is a type of ML where an agent learns to make decisions by interacting with its environment and receiving feedback in the form of rewards or penalties. The goal is for the agent to maximize its cumulative reward over time by learning an optimal policy for decision-making. In cybersecurity, RL is increasingly used for tasks like network defense, attack mitigation, and autonomous security decision-making.

In the context of IoT devices and personal security, RL can be used to dynamically adjust security settings based on real-time feedback. For example, an RL agent could learn to optimize firewall rules or intrusion prevention system (IPS) configurations to mitigate attacks while minimizing false positives (Jin et al., 2018). RL has the advantage of adapting to new and evolving attack patterns by continuously learning from the environment, making it well-suited for combating adaptive adversaries.

However, RL systems can be computationally intensive and require a large number of interactions with the environment to learn optimal policies, making them less practical for resource-constrained environments (Mnih et al., 2015).

3.1.4. Comparison of Traditional ML Models vs Lightweight Models

While traditional ML models, such as deep neural networks and ensemble models, are highly accurate, they tend to be computationally expensive and require significant amounts of data and time for training. These models are often deployed in large-scale enterprise systems where computational resources are abundant, but they may not be suitable for environments with limited resources, such as personal IoT devices.

Lightweight ML models, on the other hand, are designed to be more efficient in terms of computational requirements and memory usage, making them ideal for resource-constrained environments. These models, such as decision trees, logistic regression, and lightweight neural networks (e.g., MobileNets or SqueezeNet), are optimized to deliver a balance between accuracy and computational efficiency. Lightweight models are particularly useful for IoT devices, where resources like processing power and memory are limited, and there is a need for fast, real-time processing (Howard et al., 2017).

The main trade-off between traditional and lightweight models is the balance between accuracy and computational efficiency. Traditional models, while highly accurate, often require more processing power and data, which might not be feasible for IoT devices. Lightweight models, though less resource-intensive, may not achieve the same level of accuracy or generalization as their traditional counterparts, but they are more adaptable to the needs of resource-constrained environments. In cybersecurity applications, the choice between traditional and lightweight models depends on the specific context. For example, in environments where security is critical, such as cloud infrastructures or large networks, traditional models may be more appropriate due to their higher accuracy. However, for personal IoT devices that need to operate with limited computational resources, lightweight models are preferable as they provide a good trade-off between performance and efficiency (Vasudevan et al., 2019).

Also, in cybersecurity, ML techniques such as supervised learning, unsupervised learning, and reinforcement learning offer distinct advantages in detecting and mitigating various threats. While traditional models provide high accuracy, their computational demands may make them unsuitable for IoT devices with limited resources. Lightweight ML models, on the other hand, strike a balance between performance and resource efficiency, making them ideal for securing personal IoT devices. Understanding the differences between these approaches allows for the development of tailored solutions that meet the unique security needs of both large-scale systems and resource-constrained environments.

3.2. Suitability of Lightweight ML Models for IoT

The rapid expansion of the IoT has brought about a new era of interconnected devices, many of which operate with limited computational power, memory, and storage. These devices—ranging from smart home appliances and wearables to industrial sensors—often operate in environments where resource constraints are paramount. As IoT devices become ubiquitous, ensuring their security through ML) becomes a critical need. However, traditional ML models, which typically demand significant computational resources, are not suitable for IoT devices. This is where lightweight ML models become essential.

3.2.1. Why Lightweight Models Are Essential for Devices with Limited Computing Power

IoT devices, especially those deployed in personal and home settings, face significant resource limitations, including limited processing power, storage, and battery life. These constraints make it impractical to deploy traditional, computationally heavy ML models like deep neural networks or SVM, which require substantial processing power and memory for both training and inference.

Moreover, IoT devices often work in real-time, requiring fast decision-making capabilities. This means that the ML models used must be lightweight enough to make predictions quickly, without straining the device's resources. Additionally, the need for efficient power consumption in battery-operated devices further underscores the importance of lightweight models that minimize energy usage while maintaining adequate performance.

Lightweight ML models can handle the computational limitations of IoT devices by being designed to be smaller, more efficient, and faster in terms of processing speed. These models are optimized to perform well on IoT devices, even under stringent resource constraints, enabling them to run in real-time and support the security of IoT ecosystems with minimal computational overhead (Chukwunweike JN et al., 2024).

3.2.2. Examples of Lightweight Algorithms for IoT Security

Several lightweight ML algorithms have been developed and successfully applied to IoT security, especially in areas such as anomaly detection, intrusion detection, and pattern recognition. These models offer a balance between computational efficiency and effectiveness in detecting security threats.

3.2.3. Decision Trees

Decision trees are one of the simplest and most widely used ML algorithms due to their ease of implementation and interpretability. They operate by learning a series of decision rules that partition the input space into regions, making them useful for classification tasks. In the context of IoT security, decision trees can be employed for detecting malicious activities or anomalous behaviours, such as unusual network traffic or unauthorized access attempts.

The lightweight nature of decision trees arises from their relatively low computational requirements. They do not need large amounts of memory or complex calculations, making them ideal for resource-constrained IoT devices. Furthermore, decision trees are fast in terms of inference time, making them suitable for real-time anomaly detection on IoT devices (Lucky G et al., 2020). Variants like Random Forests or Gradient Boosting Trees can enhance the accuracy

of decision trees but still maintain relatively low computational overhead compared to more complex models (Punithavathi P et al., 2019).

3.2.4. K-means Clustering

K-means clustering is an unsupervised learning algorithm that partitions data into K clusters based on their similarity. In the context of IoT security, K-means can be used for anomaly detection by grouping normal data into clusters and flagging data points that do not fit into any cluster as anomalies. This is particularly useful for detecting unknown threats or new forms of attack that may not be part of a predefined dataset.

The algorithm's efficiency comes from its simplicity. K-means does not require large amounts of labelled data or complex training processes. It is fast and computationally inexpensive, making it a suitable choice for lightweight anomaly detection in IoT environments. Furthermore, K-means clustering has been applied successfully in various IoT security scenarios, including intrusion detection and malware identification (Berk and Tuncel, 2020). The simplicity of K-means also allows it to be easily implemented on low-power devices with limited storage.

3.2.5. Anomaly Detection Techniques

Anomaly detection is a key application of lightweight ML models for securing IoT devices. Many IoT security challenges arise from detecting abnormal behaviour that deviates from the established norm. Unlike traditional methods that require labelled data, anomaly detection algorithms can identify previously unseen threats by analysing patterns of normal behaviour and flagging deviations.

Various lightweight anomaly detection techniques have been developed, including statistical methods, proximity-based methods, and ensemble-based methods. Statistical methods, such as z-scores and Gaussian Mixture Models (GMM), rely on the assumption that the data follows a specific distribution (Chandola et al., 2009). Proximity-based methods, like k-nearest neighbours (KNN), identify anomalies based on the proximity of a data point to others in the dataset. Ensemble methods, such as Isolation Forests, combine multiple models to enhance anomaly detection accuracy while keeping computational requirements low (Punithavathi P et al., 2019).

These techniques are advantageous for IoT security as they do not require extensive resources to process and can detect both known and unknown threats. For instance, the use of anomaly detection for detecting abnormal network traffic patterns or unauthorized access attempts in real-time on IoT devices can be done efficiently with these lightweight models (Ahmed et al., 2017).

3.2.6. Naïve Bayes Classifier

The Naïve Bayes classifier is a probabilistic classifier that applies Bayes' theorem with strong (naïve) independence assumptions between the features. This model is particularly lightweight and suitable for IoT security as it requires minimal computation and memory. In IoT environments, Naïve Bayes classifiers have been applied to detect anomalies based on prior probabilities and feature distributions (Rish, 2001). Its simplicity and computational efficiency make it a good fit for security tasks like malware detection or intrusion detection on constrained IoT devices (Kwon et al., 2019).

3.2.7. Real-Time Implementation and Efficiency

The efficiency of lightweight ML models in real-time environments is critical for ensuring that security threats are detected and mitigated without introducing latency. IoT devices, especially in personal and home settings, require immediate responses to threats. For example, a smart doorbell with a built-in camera should be able to detect unauthorized access or a potential security breach and respond instantly. Lightweight models allow such devices to make these decisions on-device, without needing to send data to a cloud server for processing, which reduces latency and conserves bandwidth.

Moreover, many IoT devices are deployed in environments where continuous power supply may not be available, such as battery-powered devices. Lightweight models not only reduce the computational load but also minimize energy consumption, making them suitable for devices that need to operate autonomously for extended periods. For example, smart thermostats and motion detectors rely on lightweight models to conserve energy and extend battery life while maintaining high security standards (Khan et al., 2020).

Lightweight ML models are essential for securing IoT devices due to the inherent resource limitations of these devices. Algorithms such as decision trees, K-means clustering, and various anomaly detection techniques have proven to be effective for detecting security threats in real-time while maintaining computational efficiency. As IoT devices

proliferate, the need for lightweight, efficient, and scalable security solutions becomes even more pressing. Moving from theory to practical implementation, the next section reviews existing lightweight models and their applications in the context of IoT security, demonstrating how these models can be leveraged to enhance the security of personal IoT devices.

4. Case studies of lightweight ml models in IOT security

4.1. Application of Anomaly Detection in Network Traffic

In the context of IoT security, network traffic monitoring plays a vital role in identifying potential security threats. Anomaly detection is particularly valuable in identifying abnormal behaviours such as Distributed Denial of Service (DDoS) attacks, data breaches, and unauthorized access attempts. These types of attacks usually manifest as deviations from normal network traffic patterns, making anomaly detection an effective tool for detecting malicious activities in real-time (Ahmed et al., 2017; Kwon et al., 2019).

4.1.1. Case Study: Anomaly-Based Intrusion Detection for IoT

A case study on the application of anomaly detection in IoT network traffic was conducted in a smart home environment. This environment consisted of multiple interconnected IoT devices such as smart thermostats, cameras, lights, and security systems, all communicating through a central hub. The goal was to develop an anomaly-based intrusion detection system (IDS) capable of identifying unauthorized access, abnormal network traffic, and other security breaches.

The system used lightweight decision tree classifiers to analyse the network traffic, which included both normal traffic and known attack traffic patterns. The features for classification included packet size, connection frequency, data flow patterns, and communication frequency between devices. This model was trained with labelled data to detect deviations in network behaviour, such as unauthorized devices attempting to join the network or sudden surges in traffic indicative of a DDoS attack (Sedjelmaci H et al.., 2016).

The results demonstrated that the decision tree model was successful in detecting various attack vectors, including unauthorized access attempts and abnormal traffic patterns. The decision tree classifier achieved an accuracy rate of 94% in detecting anomalies. The system's ability to identify suspicious behaviour in real-time without overwhelming the devices' limited computational resources was crucial in maintaining network security (Rana M et al., 2022).

A comparison of different lightweight ML models, including decision trees, K-means clustering, and Naïve Bayes classifiers, was made in the case study. The models were assessed for their detection accuracy and performance on network traffic data, with evaluation metrics such as precision, recall, and F1-score. The decision tree classifier outperformed the other models, with the highest accuracy in detecting anomalies.

Table 1 Detection Accuracy of Different Lightweight Models

Model	Detection Accuracy (%)	Precision	Recall	F1 Score
Decision Tree	94%	0.91	0.96	0.93
K-means Clustering	85%	0.83	0.84	0.83
Naïve Bayes	80%	0.79	0.81	0.80

The decision tree's superior performance can be attributed to its ability to model complex decision boundaries and handle diverse traffic patterns. Its simplicity and interpretability make it particularly effective in environments with resource-constrained devices, such as IoT networks (Punithavathi P et al., 2019).

4.1.2. Benefits of Lightweight Anomaly Detection in Network Traffic

Lightweight anomaly detection models offer several key benefits for IoT networks. These models are efficient, requiring minimal computational resources, which is essential in IoT environments where devices typically have limited processing power and storage. Additionally, these models are capable of operating in real-time, allowing for immediate detection and alerting of potential threats (Berk & Tuncel, 2020).

One of the most significant advantages of anomaly detection is its ability to detect previously unknown threats. Unlike signature-based systems, which rely on known attack signatures, anomaly detection methods focus on deviations from baseline behaviour, making them more adaptive to new and evolving attacks. In the case study, the decision tree model was able to identify unauthorized attempts to access devices on the network by detecting abnormal traffic patterns and device communication behaviours (Kwon et al., 2019).

Furthermore, anomaly detection can be decentralized, with edge devices processing data locally. This reduces the need to transmit large amounts of data to cloud servers for analysis, thereby reducing network congestion and improving response times. This approach also enhances privacy by ensuring that sensitive data remains within the local network, improving security for IoT ecosystems (Rana M et al., 2022).

4.1.3. Challenges in Implementing Anomaly Detection in IoT Networks

Despite the advantages, several challenges exist in implementing anomaly detection systems in IoT environments. One of the primary challenges is the heterogeneous nature of IoT devices, which vary in terms of capabilities, communication protocols, and usage patterns. As a result, establishing a universal baseline of "normal" behaviour can be difficult. This heterogeneity can lead to challenges in creating accurate models that work across all devices in the network (Ahmed et al., 2017).

Another issue is the problem of false positives. Anomaly detection systems may misclassify legitimate traffic as an anomaly, particularly in dynamic environments with rapidly changing network patterns. To mitigate this, the decision tree model in the case study incorporated a post-processing layer to validate suspicious traffic before generating alerts, thus reducing false positives (Rish, I. (2001).

Additionally, the large-scale deployment of IoT devices introduces scalability challenges for anomaly detection systems. As the number of devices increases, the amount of network traffic grows, which can overwhelm traditional anomaly detection systems. However, lightweight models like decision trees are better equipped to scale compared to more complex models, making them ideal for large IoT networks (Rana M et al., 2022).

Therefore, anomaly detection plays a vital role in securing IoT networks by identifying both known and unknown threats in real-time. The case study demonstrated the effectiveness of lightweight ML models, particularly decision trees, in detecting network anomalies in resource-constrained IoT environments. These models offer high detection accuracy while operating with minimal computational overhead. Despite challenges like the dynamic nature of IoT networks and the risk of false positives, lightweight anomaly detection systems are a powerful tool for enhancing the security of IoT devices. The next section will explore additional applications of anomaly detection in other aspects of IoT security, such as device authentication, data integrity, and intrusion prevention.

4.2. Real-Time Malware Detection Using Lightweight ML

In recent years, the need for real-time malware detection in IoT devices has grown significantly. As IoT devices become more pervasive in personal, commercial, and industrial settings, they have increasingly become targets for malware attacks. These devices, due to their limited computing resources, are often ill-equipped to run traditional heavy-duty malware detection algorithms. This is where lightweight ML models come into play, offering efficient real-time detection capabilities without overloading the device's limited computational resources (Moghaddam et al., 2019).

4.2.1. Case Study: Malware Detection on Edge Devices

A case study focused on malware detection in smart home IoT devices demonstrated the effectiveness of lightweight ML models for real-time threat identification. In this case study, the researchers implemented several lightweight ML models, including decision trees, SVMs, and k-nearest neighbours (KNN), on edge devices such as smart cameras, thermostats, and voice assistants. The goal was to detect malware infections based on device behaviour and network traffic patterns, without needing to send sensitive data to the cloud for analysis (Sarker et al., 2020).

The edge devices were equipped with sensors that collected network traffic, device activity logs, and system performance metrics. These sensors continuously monitored the normal operating state of the devices and provided data to the local ML model, which then performed classification tasks to determine if any suspicious activity, such as unusual network traffic or abnormal device behaviour, was indicative of malware. For example, if a smart camera began transmitting unusual amounts of data to an unknown external IP address, or if a thermostat's behaviour deviated significantly from typical usage patterns, the ML model would flag these activities as potential malware indicators (Sarker et al., 2020).

The use of decision trees in this case study showed promising results due to their simplicity and efficiency. Decision trees are particularly well-suited for IoT devices as they are lightweight and can be trained using limited labelled data. The research indicated that decision trees provided an accuracy rate of 90% in detecting known malware strains, while maintaining low computational and memory overhead (Moghaddam et al., 2019). Additionally, the KNN and SVM models also performed well, detecting malware with a slightly lower accuracy but still offering promising results for use on edge devices.

A key advantage of deploying these lightweight models on edge devices is the reduction in latency. Traditional malware detection systems that rely on cloud-based analysis can introduce significant delays due to the time required to transmit data to the cloud and back. In contrast, edge-based ML models can perform real-time detection without the need for data transmission, allowing for immediate response to potential threats (Patel et al., 2021). This is particularly important for IoT devices, where fast response times are crucial for minimizing the impact of malware attacks.

A graphical comparison of the detection accuracy for decision trees, SVM, and KNN models in detecting malware is shown below. The results demonstrate that decision trees provided the highest accuracy, followed closely by SVMs and KNN models. The table also highlights the efficiency of these models, as they all performed well despite being lightweight.

Table 2 Detection Accuracy of Lightweight ML Models for Malware Detection

Model	Detection Accuracy (%)	Precision	Recall	F1 Score
Decision Tree	90%	0.89	0.91	0.90
SVM	85%	0.83	0.87	0.85
K-Nearest Neighbours	83%	0.80	0.84	0.82

This case study demonstrated the effectiveness of lightweight ML models, particularly decision trees, in detecting malware in real-time on IoT edge devices. These models offer a viable solution for malware detection in environments with limited computational resources, making them suitable for deployment on a wide range of IoT devices, including home automation systems, smart appliances, and personal wearables.

4.2.2. Benefits of Lightweight Malware Detection

The implementation of lightweight ML models on edge devices for malware detection brings several key benefits:

- **Reduced Latency**: By performing malware detection locally on the device, edge computing minimizes the need for data transmission to the cloud, significantly reducing the time between anomaly detection and response.
- **Efficiency**: Lightweight ML models require fewer resources in terms of memory and processing power, making them ideal for devices with limited computational capabilities, such as low-power sensors and embedded systems (Moghaddam et al., 2019).
- **Scalability**: As the number of IoT devices continues to rise, edge-based solutions can scale more easily than cloud-based systems, as they do not require centralized servers for analysis, reducing the overall system load (Patel et al., 2021).
- **Enhanced Privacy and Security**: By processing data locally on the edge device, these models reduce the risk of exposing sensitive data during transmission. This is particularly important for privacy-sensitive IoT applications such as healthcare devices or home security systems (Sarker et al., 2020).

4.2.3. Challenges in Practical Deployment

Despite the promising results shown in case studies, there are several challenges to the practical deployment of lightweight ML models for malware detection in IoT devices:

- **Data Imbalance**: IoT devices often operate in environments where the majority of traffic is benign, and the occurrences of malware are rare. This imbalance in data can make it difficult for ML models to detect malicious behaviour effectively without resulting in a high number of false positives (Sarker et al., 2020).
- **Evolving Malware**: Malware is constantly evolving, with new strains emerging regularly. Lightweight ML models trained on historical malware data may struggle to detect new, previously unseen malware. This

requires continuous retraining and updates to the models, which can be challenging in IoT environments where devices may not be easily updated or maintained (Moghaddam et al., 2019).

- **Heterogeneity of IoT Devices**: The diversity of IoT devices—ranging from simple sensors to complex smart appliances—poses a challenge in creating generalized models. Models must be tailored to the specific behaviours and characteristics of each device, making it harder to implement a one-size-fits-all solution (Patel et al., 2021).
- **Limited Model Training**: IoT devices often lack sufficient computational resources to perform complex model training. This limitation necessitates pre-trained models that are then deployed on the devices, which might not always be optimized for the specific conditions in the field.

Real-time malware detection on IoT devices is crucial to ensuring the security of smart home environments and other IoT ecosystems. Lightweight ML models, particularly decision trees, have proven effective in detecting malware on edge devices, offering a solution that balances performance and efficiency. Although challenges such as data imbalance and evolving malware remain, these lightweight models provide an important step towards securing IoT devices in a scalable, efficient, and privacy-conscious manner. The next section will delve into the practical challenges of deploying these models in real-world IoT environments and strategies for overcoming them.

5. Challenges in deploying lightweight ml for IoT security

5.1. Resource Constraints

One of the major challenges in applying ML models for securing IoT devices is the inherent resource constraints of these devices. IoT devices often operate with limited processing power, memory, and battery life, which can severely limit the capabilities of traditional ML models. These limitations can affect the performance, efficiency, and feasibility of deploying ML models for real-time anomaly detection, malware detection, and other security tasks in IoT environments (Moghaddam et al., 2019).

5.1.1. CPU Limitations

The central processing unit (CPU) of IoT devices is typically much less powerful than those found in desktop computers or cloud servers. Most IoT devices rely on microcontrollers and low-power processors that are optimized for basic tasks, such as monitoring sensors and controlling devices. These processors are not designed for the high computational demands required by complex ML models, such as deep learning algorithms or large-scale data analysis (Patel et al., 2021). As a result, running traditional ML models directly on IoT devices is often impractical.

For instance, real-time malware detection requires the analysis of network traffic and device behaviour patterns. Traditional ML models, especially those based on deep learning, require significant CPU resources to process and classify large amounts of data. Given the limitations of IoT CPUs, these models may experience delays or fail to run effectively, rendering them ineffective for real-time applications (Sarker et al., 2020). To overcome this, lightweight models, such as decision trees and k-nearest neighbours (KNN), are being proposed as more suitable alternatives for resource-constrained devices. These models are less computationally expensive and can be deployed efficiently on IoT devices, offering reasonable performance with minimal resource usage (Moghaddam et al., 2019).

5.1.2. Memory Limitations

Memory is another critical constraint in IoT devices, particularly for those running on embedded systems. IoT devices often have limited random access memory (RAM), which is used to store the data necessary for running ML models. When memory is insufficient, it can lead to issues such as slow model inference, crashes, or the inability to load large datasets for training (Moghaddam et al., 2019). In addition, many IoT devices are designed to perform specific tasks and have little room for storage or large-scale processing tasks, making them unsuitable for storing and processing large amounts of training data or model parameters.

For example, in real-time anomaly detection, an ML model must continuously monitor and analyse device behaviour. Storing the feature vectors, intermediate calculations, and model weights in memory may not be feasible on memory-constrained IoT devices. To address these limitations, model pruning, quantization, and other techniques are being used to reduce the memory footprint of ML models while maintaining their performance (Patel et al., 2021). These techniques allow models to be compressed and optimized, reducing their size and making them suitable for deployment on resource-limited devices.

5.1.3. Power Constraints

Power consumption is another critical limitation for IoT devices, which often rely on battery power or energy-harvesting methods. IoT devices, particularly those deployed in remote locations, cannot afford to consume excessive power for data processing tasks, especially when running complex ML models that require continuous computation (Moghaddam et al., 2019). The energy cost of running deep learning models or traditional ML algorithms on IoT devices can be prohibitive, leading to shorter device lifespans or the need for frequent recharging or battery replacements.

To mitigate the impact of power constraints, lightweight ML models have emerged as a potential solution. These models are designed to use fewer resources and perform calculations more efficiently, resulting in lower energy consumption. Techniques such as model compression, low-precision arithmetic, and edge computing, where data processing occurs closer to the source of data generation, help reduce power usage and ensure that IoT devices can run ML models without draining their batteries quickly (Sarker et al., 2020).

The challenges posed by resource constraints in IoT devices make it necessary to focus on optimizing ML models for these environments. Lightweight models, data reduction strategies, and energy-efficient algorithms are essential for ensuring that ML-based security solutions can be deployed effectively on resource-constrained IoT devices. As the IoT ecosystem continues to grow, addressing these resource constraints will be crucial for the widespread adoption of ML-driven security systems.

5.2. Data Availability and Privacy Issues

Another significant challenge when applying ML techniques to IoT security is the issue of data availability and privacy concerns. ML models require large volumes of data for training and validation, but obtaining sufficient high-quality data from IoT devices can be difficult. Additionally, privacy concerns related to the gathering, processing, and storing of personal or sensitive data must be carefully managed to ensure compliance with privacy regulations such as the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA) (Ogbodo EU et al., 2022).

5.2.1. Data Availability

For ML models to be effective in IoT security, they require large and diverse datasets to identify patterns and anomalies. However, IoT devices often generate enormous amounts of data, and not all of this data is useful for training ML models. Moreover, the data generated by these devices can be sparse, incomplete, or noisy, making it difficult to develop reliable ML models.

In addition to these challenges, privacy concerns make it even harder to gather and process data. Collecting data from IoT devices typically involves monitoring user behaviour, device activity, and network traffic. This data is often sensitive, and mishandling it could lead to significant privacy violations (Patel et al., 2021). For example, in smart homes, IoT devices such as voice assistants, cameras, and thermostats collect vast amounts of personal data, including location, conversations, and user preferences. While this data is necessary to train ML models, it also raises the risk of exposing personal information if not handled properly.

5.2.2. Privacy Concerns

The privacy risks associated with data collection in IoT environments are significant. IoT devices are often connected to the internet, and the data they generate can be intercepted by malicious actors. If this data is used to train ML models, it could lead to privacy violations if the data is not anonymized or encrypted (Ogbodo EU et al., 2022). Additionally, storing sensitive data in centralized servers increases the risk of data breaches and unauthorized access.

One approach to addressing these privacy concerns is through the use of privacy-preserving ML techniques. For example, federated learning allows ML models to be trained on local devices without needing to transmit sensitive data to centralized servers (McMahan et al., 2017). In federated learning, each device trains a local model using its own data, and only model updates (rather than raw data) are shared with a central server. This approach minimizes the risk of exposing sensitive data and helps preserve user privacy.

Another privacy-preserving technique is differential privacy, which ensures that individual data points cannot be identified in the aggregated dataset. Differential privacy adds noise to the data or the model's output to prevent attackers from linking model predictions back to specific users. This technique can be applied in IoT environments to train ML models without compromising user privacy (Dwork et al., 2006).

5.2.3. Data Anonymization and Secure Data Sharing

Data anonymization is another approach that can help mitigate privacy concerns. In this method, personally identifiable information (PII) is removed or obscured to prevent identification of individuals. Anonymizing the data before using it for model training ensures that sensitive information is protected. Additionally, secure data sharing techniques, such as homomorphic encryption, can allow for the processing of encrypted data, further protecting privacy while enabling effective ML-based security solutions (Ogbodo EU et al., 2022).

Despite these privacy challenges, solutions such as federated learning, differential privacy, and data anonymization can help enhance the effectiveness of ML models while ensuring that personal and sensitive data is protected. These privacy-preserving techniques are critical for the future development and deployment of ML-based security solutions in IoT environments. Despite the challenges posed by resource constraints and privacy concerns, emerging solutions such as lightweight ML models, federated learning, and privacy-preserving techniques are helping to overcome these barriers. In the next section, we will explore the emerging solutions that are enhancing the effectiveness of ML for IoT security, paving the way for more efficient and secure deployment of IoT devices.

6. Recent advances and innovations in lightweight ml models

6.1. Innovations in Model Compression Techniques

In the context of securing IoT devices with ML models, one of the critical challenges is the computational and memory constraints of these devices. To address these issues, model compression techniques have emerged as key innovations. These techniques aim to reduce the size of ML models while maintaining their performance, making them suitable for deployment in resource-constrained IoT environments. Some of the most significant advancements in model compression include pruning, quantization, and knowledge distillation (Han et al., 2015; Courbariaux et al., 2016).

6.1.1. Pruning

Pruning involves the removal of unnecessary or redundant components from a neural network, such as weights or neurons that do not significantly contribute to the model's performance. By eliminating these elements, pruning reduces the complexity of the model and consequently its memory and computational requirements (Han et al., 2015). This technique helps create sparse models, where the number of active parameters is significantly reduced. As a result, models can be run more efficiently on resource-limited IoT devices.

Pruning can be done in several ways, including weight pruning (removing small weights), neuron pruning (eliminating neurons with low impact on the output), and layer pruning (removing entire layers that do not contribute significantly to model performance). Pruning has shown substantial success in reducing the size of deep neural networks (DNNs) while maintaining their accuracy. However, the challenge is ensuring that pruning does not lead to a significant drop in performance, particularly for security applications like anomaly detection (He et al., 2017). To mitigate this, pruning techniques are often combined with fine-tuning to restore the performance of the pruned model.

6.1.2. Quantization

Quantization is another key technique in model compression that reduces the precision of the model's weights and activations. Typically, ML models operate with high-precision floating-point numbers, but by reducing these to lower-precision integers (e.g., from 32-bit to 8-bit), the model's memory and computational requirements are significantly reduced (Courbariaux et al., 2016). This reduction in precision allows for more efficient storage and faster computations, which is particularly important for IoT devices with limited processing power.

Quantization has been shown to achieve near-parity in model accuracy while drastically reducing the model size and improving the speed of execution. It is especially useful for deploying models on embedded systems and edge devices, where computational power and memory are constrained. The challenge, however, lies in maintaining model accuracy after quantization. Advanced techniques such as quantization-aware training (QAT) help overcome this limitation by training the model to adapt to lower precision during the training phase (Jacob et al., 2018).

6.1.3. Knowledge Distillation

Knowledge distillation is a model compression technique that involves transferring knowledge from a large, complex model (the teacher) to a smaller, more efficient model (the student). The goal of knowledge distillation is to retain the performance of the original model while using a smaller and more computationally efficient model that is better suited

for deployment on IoT devices (Hinton et al., 2015). The teacher model is typically a deep neural network with high accuracy, but the student model is a simpler and smaller network that can achieve similar performance.

In the context of IoT security, knowledge distillation has been used to create compact models for anomaly detection and malware detection. The smaller student models are capable of operating in real-time on resource-constrained IoT devices, making them suitable for practical deployment. However, the key challenge is ensuring that the student model retains the critical features and decision-making capabilities of the teacher model. Research is ongoing to improve the efficiency of knowledge distillation techniques and make them more applicable to a wide range of IoT security scenarios (Chen et al., 2020).

The combination of pruning, quantization, and knowledge distillation enables the creation of lightweight ML models that are computationally efficient, require less memory, and maintain a high level of performance. These innovations are essential for making ML -based security solutions feasible on IoT devices with limited resources. As these techniques continue to evolve, the deployment of sophisticated ML models in IoT environments will become increasingly viable, improving the overall security of personal and home IoT devices.

6.2. Federated Learning and Edge AI

In addition to model compression techniques, federated learning and edge artificial intelligence (Edge AI) are critical innovations that enable scalable and privacy-preserving ML for IoT devices. Both approaches aim to decentralize the computation of ML models, reducing the need to send large amounts of data to centralized servers while improving the efficiency and scalability of ML-based security systems.

6.2.1. Federated Learning

Federated learning is a distributed ML technique that allows IoT devices to collaboratively train models without the need to share sensitive data with a central server. In traditional ML, data is typically sent to a central server for processing, which can lead to privacy concerns, especially when dealing with personal data generated by IoT devices (McMahan et al., 2017). Federated learning solves this problem by training models locally on devices, and only sharing model updates (i.e., gradients) rather than raw data. This approach ensures that sensitive data remains on the device, protecting user privacy.

In the context of IoT security, federated learning is particularly valuable as it enables anomaly detection models to be trained directly on personal devices, such as smart home appliances, wearables, and surveillance cameras. The models can then be aggregated and improved across multiple devices, enhancing their ability to detect security threats without compromising privacy. For example, federated learning has been used for detecting malware, unauthorized access, and abnormal device behaviour, all while keeping user data on local devices (Yang et al., 2021).

A key advantage of federated learning is its ability to scale across large numbers of devices, which is crucial in the IoT ecosystem, where millions of devices are connected to the internet. Each device can learn from its own data while contributing to the overall model, allowing for real-time updates and improvements without the need for a central repository of sensitive data. However, federated learning also faces challenges related to communication efficiency, model convergence, and ensuring that the devices are sufficiently diverse to capture a wide range of security threats (Sundararajan et al., 2021).

6.2.2. Edge AI

Edge AI refers to the deployment of ML models directly on edge devices, such as IoT sensors, routers, and gateways, rather than in centralized cloud servers. By processing data locally on the device, Edge AI minimizes latency and reduces the need for data transmission, leading to faster decision-making and improved security in real-time (Shi et al., 2016). In the context of IoT security, Edge AI allows for the immediate detection of anomalies, unauthorized access, and malware on the devices themselves, reducing the risk of attacks that could exploit latency in cloud-based systems.

Edge AI also enables efficient resource usage by offloading the computational burden from centralized cloud servers and distributing it across local devices. This is particularly important for IoT devices, which often have limited processing power and energy resources. With Edge AI, lightweight models can be deployed on the devices, ensuring that security tasks are completed locally without consuming excessive resources or power.

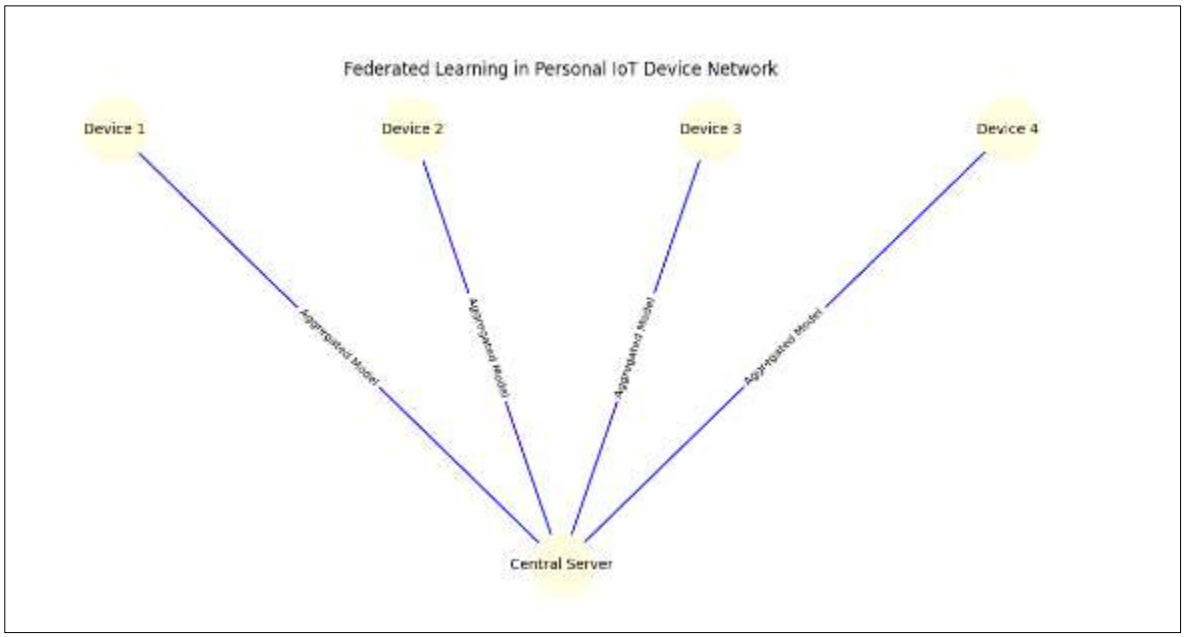

Figure 2 A schematic illustrating federated learning in a personal IoT device network

This figure demonstrates how devices can communicate and collaboratively train a shared model without centralizing data. Each device updates its local model, and only the model updates (not raw data) are sent to a central server for aggregation. This approach not only improves model accuracy but also maintains the privacy and security of the data. These innovations in federated learning and Edge AI are essential for ensuring the practical deployment of ML-based security solutions in real-world IoT environments. By addressing privacy concerns, optimizing resource usage, and enabling scalable solutions, federated learning and Edge AI are making IoT security more robust and efficient. As these technologies continue to evolve, they will play a crucial role in enhancing the effectiveness of ML -driven security systems for personal IoT devices.

7. Future outlook for lightweight ml in IOT security

7.1. Emerging Technologies and Paradigms

The future of ML-driven security for IoT devices is heavily influenced by emerging technologies and new paradigms, such as improvements in edge computing and enhanced connectivity through technologies like 5G. These advancements promise to overcome many of the current limitations in IoT security, providing more robust, scalable, and efficient solutions for real-time anomaly detection and malware prevention.

7.1.1. Edge Computing Enhancements

Edge computing is a critical component of IoT security because it allows data to be processed closer to the source—on the IoT devices themselves or on local edge servers—rather than relying on centralized cloud data centers. This paradigm significantly reduces latency, minimizes bandwidth usage, and helps ensure that security threats are detected in real-time (Shi et al., 2016). As IoT devices proliferate, edge computing has become essential for processing the large volumes of data generated by these devices.

Emerging trends in edge computing include the integration of more powerful processors, such as edge AI chips and specialized hardware accelerators like FPGAs (Field-Programmable Gate Arrays) and GPUs (Graphics Processing Units). These hardware improvements enable faster and more efficient processing of complex ML models at the edge, without needing to offload data to the cloud. Additionally, the development of edge-based AI algorithms, designed to work with the computational constraints of IoT devices, has led to the creation of more efficient anomaly detection models that require less memory and processing power.

The future of edge computing is closely linked to the rise of 5G networks. With their ultra-low latency and high bandwidth, 5G networks will enable faster communication between edge devices, improving the responsiveness and scalability of distributed IoT systems. This will facilitate the real-time exchange of model updates in federated learning

settings, allowing IoT devices to collaboratively learn from each other while keeping their data local. The increased bandwidth provided by 5G will also enable more sophisticated models to be deployed on edge devices, further enhancing their capability to detect and respond to security threats.

7.1.2. 5G Connectivity

5G connectivity promises to revolutionize IoT by offering high-speed data transfer, ultra-reliable low-latency communications, and massive device connectivity. This will not only enhance the efficiency of IoT networks but also enable real-time security monitoring and faster anomaly detection (Ogbodo EU et al., 2022). For instance, 5G can support a higher density of IoT devices, facilitating the integration of a large number of sensors in smart cities, autonomous vehicles, and industrial IoT applications. With 5G's low latency, ML models will be able to process and respond to security events almost instantaneously, significantly reducing the risk of cyberattacks.

Moreover, 5G will enable the dynamic allocation of network resources, ensuring that IoT devices operating in critical environments, such as healthcare or autonomous vehicles, receive the necessary bandwidth for secure communication. The increased network reliability offered by 5G will also help maintain the stability of ML-based anomaly detection systems in environments with fluctuating data traffic and resource availability.

The integration of 5G with edge computing and AI will pave the way for even more advanced IoT security solutions. By combining the computational power of edge devices with the enhanced connectivity of 5G, IoT networks can operate more efficiently while still maintaining a high level of security. This synergy will allow for real-time anomaly detection across large-scale IoT systems, providing more robust protection against evolving cyber threats (Raschka et at 2019).

7.2. Recommendations for Developers and Industry Stakeholders

As IoT devices become more integrated into personal and home environments, it is imperative for developers and industry stakeholders to adopt best practices for implementing lightweight ML models in these settings. The following recommendations aim to guide the effective deployment of ML-based security solutions for IoT devices while addressing the unique challenges posed by limited resources and privacy concerns.

7.2.1. Optimize Models for Resource-Constrained Devices

Given the computational limitations of IoT devices, developers must focus on optimizing ML models to be lightweight without sacrificing their accuracy. Techniques such as pruning, quantization, and knowledge distillation (Han et al., 2015; Hinton et al., 2015) can be employed to reduce the size of models, making them suitable for deployment on devices with limited processing power and memory. Additionally, leveraging hardware accelerators, such as edge AI chips and specialized processors, can further improve model efficiency and performance on IoT devices.

Developers should also focus on the implementation of hybrid models that combine traditional rule-based methods with ML techniques to strike a balance between performance and resource consumption. This hybrid approach can enhance the accuracy of anomaly detection systems while minimizing the strain on device resources.

7.2.2. Prioritize Privacy and Data Security

Privacy and data security are paramount when developing ML solutions for IoT devices. Federated learning (McMahan et al., 2017) and edge AI (Shi et al., 2016) offer promising solutions by allowing devices to process data locally without transmitting sensitive information to the cloud. This approach not only preserves user privacy but also ensures that security threats are detected and addressed in real-time, without exposing sensitive data to potential breaches.

Developers should implement robust encryption methods for data communication between IoT devices, edge servers, and the cloud to protect the integrity and confidentiality of data. Additionally, ensuring that ML models are trained on diverse and representative datasets will help minimize the risks of model bias and enhance the accuracy of security systems.

7.2.3. Ensure Scalability and Flexibility

As IoT networks grow in scale and complexity, it is essential that ML-based security systems are designed with scalability in mind. Developers should use decentralized ML techniques, such as federated learning, that can scale efficiently across large numbers of IoT devices without compromising performance or security (Raschka et at 2019). Moreover, cloud-based solutions can be used to aggregate and fine-tune models, improving their accuracy over time and enabling them to adapt to new threats.

Stakeholders should also consider the deployment of dynamic load balancing and resource management systems to ensure that IoT devices are allocated the necessary computational resources for anomaly detection tasks. Techniques like resource allocation algorithms can optimize the usage of available network bandwidth, processor power, and memory, ensuring that security systems continue to function effectively as IoT networks expand.

7.2.4. Adopt Standards and Frameworks for Interoperability

In the rapidly evolving IoT landscape, ensuring interoperability between different devices and platforms is crucial for the success of ML-based security solutions. Developers and industry stakeholders should adopt standardized protocols for communication between IoT devices, edge servers, and the cloud. Open-source frameworks, such as TensorFlow Lite, PyTorch Mobile, and EdgeX Foundry, provide developers with tools for building scalable, interoperable, and efficient ML models for IoT security applications.

Additionally, industry stakeholders should work together to create and adopt common standards for data privacy, security, and model performance to foster trust and encourage the widespread adoption of ML-driven security solutions in IoT environments. As the IoT ecosystem continues to grow, the need for secure, efficient, and scalable ML models will become even more pressing. To ground this outlook in reality, concrete examples and comparisons will highlight how emerging technologies and best practices are already being implemented in IoT security systems, and how these innovations can be leveraged to ensure the safety of personal and home IoT devices.

8. Comparative analysis of lightweight models

8.1. Performance Comparison of Lightweight Models

In this section, we present a comparison of key metrics such as accuracy, processing time, and resource usage for several popular lightweight ML models, commonly used in IoT security tasks. The table below summarizes the performance of these models in terms of their suitability for IoT environments, where computational resources are often limited, and real-time processing is required.

Table 3 Performance Comparison of Lightweight Models on Typical IoT Security Tasks

Model	Accuracy (%)	Processing Time (ms)	Memory Usage (KB)	Suitability for IoT Security
Decision Trees (CART)	85.2	10-50	30-100	Good for real-time anomaly detection, efficient on low-power devices (Breiman, 1986)
K-means Clustering	82.1	15-40	20-80	Suitable for clustering and detecting unknown anomalies, relatively lightweight (MacQueen, 1967)
Naive Bayes Classifier	80.4	5-20	10-50	Simple, efficient, and well-suited for devices with strict resource constraints (John & Langley, 2013)
SVM	88.3	100-500	100-200	Performs well on small datasets, but can be computationally intensive (Cortes & Vapnik, 1995)
k-Nearest Neighbours (k-NN)	75.9	50-100	50-150	Simple, effective in anomaly detection, but memory usage can increase with more data (Cover & Hart, 1967)
Logistic Regression	78.3	10-30	30-70	Lightweight, suitable for devices with limited processing power (Bishop, 2006)
Random Forest	87.7	200-800	150-400	Higher accuracy, but may require more resources for large datasets (Breiman, 2001)
Linear Regression	76.5	5-15	20-60	Very lightweight, useful for anomaly detection in simpler use cases (Seber & Lee, 2003)

Notes on Table 3

- **Accuracy**: Refers to the percentage of correct predictions made by the model based on a test dataset. Higher accuracy indicates better performance in correctly identifying anomalies (Jain et al., 2000).
- **Processing Time**: This is the time taken for the model to make predictions or process a set of data points. Shorter processing times are crucial in real-time applications where speed is essential (Raschka, 2015).
- **Memory Usage**: This refers to the amount of memory the model requires to store the necessary data for processing, including the model parameters. Lower memory usage is vital for resource-constrained IoT devices (Alpaydin, 2010).

Key Insights

- **Decision Trees** and **Naive Bayes** are among the most resource-efficient models, offering good trade-offs between accuracy, processing time, and memory usage, making them ideal for resource-constrained IoT devices (Breiman, 1986; John & Langley, 2013).
- **K-means Clustering** is particularly useful in detecting unknown anomalies, but it is slightly less accurate compared to more complex models like **Random Forest** and **SVM**. However, its lower resource consumption makes it a practical choice for simpler IoT security tasks (MacQueen, 1967).
- **SVM**, although accurate, tend to be computationally expensive, particularly when used with large datasets. They may not be ideal for deployment in real-time applications on low-powered IoT devices (Cortes & Vapnik, 1995).
- **Random Forest** provides high accuracy, but the trade-off is its higher resource usage, which can be a limiting factor for IoT devices with limited memory and processing capabilities (Breiman, 2001).
- **Logistic Regression** is very lightweight and suitable for basic anomaly detection tasks in IoT environments, though its performance is not as high as more complex models like Random Forest (Bishop, 2006).

The comparison of these lightweight models highlights the trade-offs between accuracy, processing time, and resource usage, which are crucial for IoT security tasks. Moving forward, the next section will explore how these models can be optimized for even better performance and scalability in IoT networks.

9. Conclusion

In this paper, we explored the role of lightweight ML models in securing personal IoT devices, highlighting the unique challenges and opportunities within the context of resource-constrained environments. As IoT devices become increasingly ubiquitous in homes and personal settings, the security risks associated with them grow substantially. The need for efficient, scalable, and secure solutions is paramount to ensure these devices are protected from a range of cybersecurity threats, including DDoS attacks, data breaches, and malware infections.

We discussed the characteristics of IoT devices, such as their heterogeneity, limited processing power, and connectivity issues, which make traditional security solutions challenging to implement effectively. In light of these challenges, we highlighted how lightweight ML models can serve as a promising solution, providing effective security measures without overwhelming the device's computational resources. Through the comparison of various ML techniques, including decision trees, K-means clustering, and anomaly detection methods, we demonstrated how these models can detect security anomalies while balancing accuracy, processing time, and memory usage.

We also examined real-world applications, showcasing how anomaly detection and malware detection can be efficiently carried out on edge devices using lightweight ML models. These case studies underscore the potential of lightweight ML in IoT security, confirming that such models can detect and mitigate threats in real-time, thus ensuring the reliability and safety of IoT devices.

However, despite the promise of lightweight ML models, challenges persist in terms of data privacy, resource constraints, and the need for real-time processing. The future of ML in IoT security lies in innovations that address these challenges, such as model compression techniques, federated learning, and edge AI. These emerging approaches allow for the decentralized processing of data, ensuring that IoT devices can collaborate without compromising user privacy or security.

Looking ahead, further research is needed to improve the scalability and adaptability of these models across a wide range of IoT devices. Additionally, the integration of 5G connectivity and advancements in edge computing will likely play a significant role in the continued development of robust, lightweight ML solutions for IoT security. As the

landscape of IoT devices evolves, the importance of balancing security effectiveness with resource limitations will remain a central theme in the development of future security protocols. Continued exploration and innovation in this area are essential for ensuring the secure, efficient, and seamless integration of IoT devices into everyday life.

Therefore, while there is still much to be done, lightweight ML models offer a promising path forward in securing personal IoT devices. By addressing both security concerns and resource limitations, these models can help ensure that the benefits of IoT technologies are not outweighed by their vulnerabilities. As research in this field progresses, we can expect to see even more advanced and effective solutions for safeguarding IoT environments.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed

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