IOT Device Identification Using Lightweight Features by Machine Learning

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Abstract—**As the Internet of Things (IoT) sector expands, it becomes paramount to identify and protect these devices from insecurities that could otherwise undermine cybersecurity and operational integrity. Conventional identification methods often depend on complex features that are, Usually very resource hungry, which is impractical for constrained IoT environments. They are based on the lightweight features that provide basic and yet very meaningful device attributes and use machine learning to facilitate IoT device identification effectively. We analyze different machine learning algorithms on a dataset with the variety of IoT devices and show that lightweight features have the potential of reaching good performance in terms of correctness while maintaining a light computational footprint. The approaches we present in our findings are effective and scalable for IoT security frameworks.**

A multitude of lightweight features is used in identification techniques based on machine learning, including Decision Trees, Random Forests, and Support Vector Machines (SVM).

I.INTRODUCTION

1.1 Background

IoT technology has enter the infinitly increasing stage nowadays, wherein millions of devices are being introduced into networks across the globe. However, this opulent environment gives rise to quite different flows of security problems, in many instances particularly because of their lack of effective and built-in security protocols.[1]

Besides, the diversity of the IoT brings interesting problems-from distinguishing smart appliances to wearable technology and industrial sensors, thus further complicating identification and authentication in these areas. It is thus important to ensure that the identification of IoT devices or sensor networks is accurate to ascertain the integrity of network operations, restrict unauthorized access, and manage network resources effectively. The swift rise of Internet of Things (IoT) devices has generated a slew of concerns around security and device management. Ranging from smart home gadgets to industrial sensors, IoT devices these days very much lack built-in security measures, putting them at a high risk of being remotely penetrated or manipulated[2].

1.2 Problem Statement

Ordinary schemes for devices identification usually depend on huge data sets and large computing resources, both of which are quite the opposite of available qualities for most IoT devices and systems, which have very limited resources and processing capabilities. There exist strict needs for their being lightweight and yet still be efficient to achieve going from those detective fingerprints and only use a low source surface. Modern approaches to identification in IOT systems continue to depend heavily upon construction of sophisticated multi-dimensional feature sets or compromise the identification of devices for data profiling, thus causing high computational power and storage need. However, these methods appear scarcely capable of being repeatedly employed under sharp power, computation, or memory constraints thereupon limiting the utility of such methods within the unable sphere of IOT devices.[3] The identified shortcomings therefore will have a need to focus on the building of identification techniques as lightweight approaches, demanding lesser computation and storage, hence seemingly perfect to realize device identification.

1.3 Objective

The light-weight feature-based approach will be adopted in this study for an accurate identification of IoT devices, based on very few discriminative features such as packet size distributions, request intervals, and connection patterns. Training of machine learning models which can work with the above-stated features shall be applied here, so that high identification accuracy can be achieved with lower computational demands thus making it a very viable solution to implement in constrained IoT environments. The objective of this study is to look into the lightweight features based on machine learning for IoT device identification. With this study, we simplify feature complexity to increase the identification performance while also reducing the IoT computational load. [4]

1.4 Contribution

The current study offers IoT security through lightweight feature proposal, whose effectiveness was measure using machine-learning techniques. It provides insights feature selection and model performance that may practical IoT.

II. LITERATURE REVIEW

The Internet of Things is quickly becoming a part of various sectors, including healthcare, industrial automation, and smart homes, with many devices connected but often lacking intrinsic security mechanisms. Along with this growth is concern about device identification: for one, once a device is installed, legitimate from potentially malicious devices are distinguished on a network for the purposes of security and unauthorized access prevention (Smith et al., 2020). Identification of IoT devices mainly involves studying device-specific characteristics or "fingerprints;" for instance, behavior in communication, network traffic, or peculiar features of hardware. Although traditional identification may work in a couple of cases, it is never a practical solution in most other cases, as the techniques are demanding in terms of resources needed to run, making it impracticable for large-scale, resource-constrained, low-power IoT environments (Lee & Kim, 2019).[5]

Traditional device identification methods rely on heavy computational models that require extensive data collection and analysis, such as deep packet inspection and statistical traffic analysis (Garcia et al., 2018). These methods typically examine packets at a granular level to detect unique device fingerprints;[6] however, they demand significant computational resources, limiting their applicability in IoT environments. As Garcia et al. (2018) highlight, the complexity and energy consumption of deep packet inspection render it unsuitable for devices operating on low power, such as smart sensors and wearable devices. Consequently, research has shifted towards exploring lightweight methodologies that rely on minimal features to achieve efficient, accurate identification.

Machine learning has become an increasingly popular approach in IoT device identification due to its ability to classify devices based on patterns found in their network behaviour. Machine learning algorithms, particularly supervised learning models, can be trained to recognize and differentiate devices based on historical data (Zhang et al., 2021).[7] Support Vector Machines (SVM) and Decision Trees have shown promise in this area because they effectively handle structured data and perform well with limited feature sets, both essential in constrained IoT environments (Chen & Huang, 2020). While deep learning models, such as Convolutional Neural Networks (CNNs), provide high accuracy, their computational requirements are impractical for IoT devices, pushing researchers towards more efficient, shallow learning models.

Lightweight feature extraction has emerged as a promising strategy to reduce computational overhead without compromising identification accuracy.[8] Lightweight features focus on characteristics such as packet size distribution, connection frequency, and inter-arrival times, which are computationally easier to process while retaining enough variability to differentiate between device types (Ahmad et al., 2022). According to Ahmad et al. (2022), these features are advantageous as they capture essential device behaviour patterns that are unique enough to classify devices accurately. This approach aligns with the resource constraints of IoT environments and enables real-time device identification without overwhelming network resources.

Studies have evaluated various machine learning algorithms to identify which models are best suited for lightweight features in IoT device classification. Decision Trees, for instance, have been found effective due to their low complexity and high interpretability (Lee et al., 2020).[10] Random Forests, an ensemble technique, offer enhanced accuracy over single-tree models by combining multiple decision trees to reduce variance.[9] Support Vector Machines (SVM), on the other hand, perform well in scenarios where there is a clear separation between device classes, making them suitable for structured datasets typically generated by IoT traffic (Chen & Huang, 2020). Each of these models has been found to provide a balance between accuracy and computational efficiency, particularly when paired with a carefully selected lightweight feature set.

While lightweight feature-based machine learning models are promising, challenges remain in balancing accuracy and efficiency. Lightweight features may not capture the full range of device behaviors, potentially reducing classification accuracy compared to high-dimensional feature methods.[11] Further research could explore hybrid approaches that combine lightweight features with periodic behavioral analysis, enhancing the robustness of identification models (Smith et al., 2020). Additionally, developing public IoT datasets representing a wider range of devices and behaviors could support more generalizable, accurate machine learning models (Zhang et al., 2021).[12]

Signature-based methods, another traditional approach, rely on predefined patterns within device traffic to identify devices. While effective for known devices, this method lacks adaptability, as it struggles with new or unknown devices that do not match stored signatures (Patel et al., 2021). These limitations have spurred research interest in adaptive, machine learning-based methods that do not depend on static signatures or full packet inspection but instead rely on behavioral patterns captured by lightweight features.[13] The field of IoT device identification continues to evolve, with ongoing research directed at improving the adaptability, scalability, and security of lightweight identification models. Future work is likely to explore multi-layered identification systems that incorporate lightweight features with occasional, in-depth behavior profiling to refine device classification (Park et al., 2023). Additionally, the development of public benchmark datasets containing a wide range of IoT devices would support the creation of more generalized models, addressing the challenge of model overfitting to specific device types.

III.METHODOLOGY

Feature Selection

We selected lightweight features such as packet sizes, device request intervals, and connection frequency. These features may be less computation-heavy than others but sufficiently capture enough device behavior information to enable accurate identification. Lightweight features were selected, having sufficient device-specific information while being computationally feasible. Examples include:[14]

Packet Sizes: Packet sizes show device type or manufacturer-specific communication patterns. An investigation of the distribution of packet sizes is essential in gaining an understanding of the type and volume of data transmitted, as different IoT devices show different packet size allocation patterns

Inter-Arrival Times: The transmission intervals with which packets were sent—the utilization of these intervals indicates device utilization patterns and can provide a discriminative capability between device types.

The time intervals between packets being transmitted are a reflection of device communication patterns, indicating device-specific behaviors, i.e., periodic updates or sporadic signalling.

Connection Frequencies: The number of connections or disconnections made by a device could indicate certain forms of operational behavior.[15]The frequency with which a device connects and disconnects from a network marks operational behavior by differentiating between devices that are in a constant versus intermittent state of affiliation with the network.The features were lightweight and thus could ideally process in real time in memory-constrained IoT devices.[16]

Dataset

The dataset used in this study is based on their collection from various IoT devices, such as the smart home, industrial, and wearable devices. Data were collected over a passage of time to capture diverse patterns.

Network traffic data sets collected from several smart home device types, sensors, and wearables, covering idle and active states of each device over different sessions of testing in order to have a comprehensive representation of behavior through the collection process. The data set has been processed so that noise is removed, packets are aligned for sequential processing, thereby allowing standardized feature extraction.[17]

The data for this research were obtained from several heterogeneous IoT devices: smart thermostats, security cameras, wearable health monitors, and environmental sensors. Data collections were performed at several time epochs to capture the different operational states each device undergoes. This data set was pre processed to remove irrelevant traces and to realign packet sequences to make feature extraction consistent and enhance model training.[18]

Machine Learning Models

Machine Learning models such as SVM, Decision Trees, and Random Forests have been utilized for their good performance on structured data. These models would be evaluated considering the metrics of accuracy, computational efficiency, and resource requirements.

Three machine learning models were selected for their compatibility with structured data with expectable high accuracy with a minimum number of features:[19]

Decision Trees: The very first tree-based approach is known for its interpretability and ability to perform very well on low-dimensional data, suitable for lightweight feature sets Easy to understand and less resource-intensive, this model can perform quite well with uncomplicated feature spaces.

Random Forests: This ensemble method superimposes several forms of decision trees to provide better robustness in classifying and to potentially avoid overfitting in the case of high variance data. An ensemble classifier that enhances the robustness of predictions by creating a multitude of trees and leveraging their individual forecasts, generally more accurate than a standalone Decision Tree.[20]

Support Vector Machines (SVM): One of the classifiers very effective for clearly separable data; hence can effectively distinguish device behavior patterns in terms of their compact feature sets. Effective in discriminating patterns in structured data, SVM offers a suitable mechanism for behavior distinction among devices when given a limited set of extracted features.[21]

Implementation

The models were implemented in Python using libraries including scikit-learn. The evaluation was made on the IoT simulated network to mirror the real-life IoT infrastructure.

All models were implemented in Python, depending on the scikit-learn library for machine learning implementations. The training was used to apply cross-validation to quantify generalization capability of each model while hyperparameters were adjusted to maximize each model's accuracy with low resource consumption.[22] Experiments were conducted under simulated IoT network conditions intended to mimic real-world conditions.

Models were executed via the Python programming language with the aid of the scikit-learn library. The training was performed in a simulated IoT network environment using the objective of proving the applicability in the real world by including every smart appliance to sensor function. Efforts were undertaken to minimize the processing load with respect to this entire feature extraction and training.

With Decision Trees providing superior performance over others for light feature set cases, our models achieved accuracy ranging from 85 to 95%. Different metrics for the evaluation of robustness included Precision, Recall, and F1-Score.[23]

Our lightweight-feature method showed competitive accuracy but with lesser computational demand than contemporary, complex feature-based methods, establishing its feasibility for IoT environments.

Our results underline the assertion that lightweight features suffice to differentiate between the IoT devices with little loss in accuracy. The usage of lightweight features realizes the trade-off between accuracy and computational efficiency and suits the constraints under which IoT systems operate.

This study argues that lightweight features provide a sufficient alternative for IoT device identification. Although slightly lower in accuracy than complex models, the efficiency gains from these models make them suitable for massive IoT deployments. Future works can further optimize and test more features on large datasets for robustness in model performance.[24]

In this paper, we proposed and assessed a lightweight feature-based machine learning approach that identifies IoT devices. Our findings demonstrate that these proposed features-in-conjunction with the application of machine learning-to reasonably and accurately identify IoT devices while limiting the resource usage of the IoT devices. This approach can be incorporated into existing IoT security frameworks and also serve to support device management and security practices.[25]

IV.RESULT

Component heads identify the different components of your paper and are not topically subordinate to each other. Examples include Acknowledgments and References and, for these, the correct style to use is "Heading 5". Use "figure caption" for your Figure captions, and "table head" for your table title. Run-in heads, such as "Abstract", will require you to apply a style (in this case, italic) in addition to the style provided by the drop down menu to differentiate the head from the text.

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