Can Evil IoT Twins Be Identified? Now Yes, a Hardware Behavioral Fingerprinting Methodology

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Abstract—The connectivity and resource-constrained nature of single-board devices opens up to cybersecurity concerns affecting Internet of Things (IoT) scenarios. One of the most important is the presence of evil IoT twins. Evil IoT twins are malicious devices, with identical hardware and software configurations to authorized ones, that can provoke sensitive information leakages, data poisoning, or privilege escalation in IoT scenarios. Combining behavioral fingerprinting and Machine/Deep Learning (ML/DL) techniques is a promising solution to identify evil IoT twins by detecting minor performance differences generated by imperfections in manufacturing. However, existing solutions are not suitable for single-board devices because they do not consider their hardware and software limitations, underestimate critical aspects such as fingerprint stability, and do not explore the potential of ML/DL techniques. To improve it, this work proposes an ML/DL-oriented methodology that uses behavioral fingerprinting to identify identical single-board devices. The methodology leverages the different built-in components of the system, comparing their internal behavior with each other to detect variations that occurred in manufacturing processes. The validation has been performed in a real environment composed of identical Raspberry Pi 4 Model B and Raspberry Pi 3 Model B+ devices, obtaining a 92.6% average accuracy with a Random Forest model and achieving the identification for all devices by setting a 50% threshold in the evaluation process. Finally, a discussion compares the proposed solution with related work and provides important lessons learned and limitations.

Index Terms—Device Behavior Fingerprinting, Device Identification, Cyberattack Detection, Behavioral Data, Hardware Fingerprinting

I. INTRODUCTION

The diversity of IoT devices in modern scenarios is huge, but single-board devices, such as Raspberry Pi, have gained enormous prominence due to their flexibility, reduced price, broad support, and peripherals availability. Unfortunately, the connectivity and resource-constrained nature of single-board devices, and IoT in general, opens the door to numerous cybersecurity concerns affecting heterogeneous platforms [1]. One of the most important cybersecurity concerns affecting IoT is the presence of unauthorized devices with the same hardware and software configuration as authorized nodes. These malicious devices, called evil IoT twins, can be articulated by several well-known cyberattacks [2], such as device spoofing, occurring when an attacker replaces a legitimate sensor or actuator with a malicious device using the same identity; unauthorized device deployment, related to the deployment of a new device in the platform which is using an unregistered identity; and Sybil attack, referring to a malicious device using numerous identities to simulate being several devices. Besides, other cybersecurity threats, such as sensitive information leakage, data poisoning, or privilege escalation and lateral movements, might arise as a consequence of evil IoT twins.

The identification of single-board devices with identical hardware and software configuration is a potential solution to the previous cybersecurity concern but still an emergent and open challenge. In such a context, there is no work focused on identical single-board device identification. However, for other devices without component and resource limitations, the literature has proposed the usage of behavioral fingerprinting as a promising solution to detect minor performance differences generated by imperfections occurred during the devices manufacturing process.

In particular, existing work focuses on crystal oscillator impurities and cut variations that generate imperfect frequency outputs in components such as CPU or GPU to detect performance differences in identical devices [3]. Current solutions consider dimensions such as clock-slew analysis, Physical Unclonable Functions (PUFs), or execution time and performance analysis. However, despite their benefits, the following challenges are still open: i) there is no common methodology for identifying identical devices based on their hardware; ii) existing solutions are designed for traditional computers, being not suitable for IoT environments with single-board devices having software and hardware restrictions (as discussed in Section 12); iii) most of the existing solutions have been tested missing essential factors affecting the identification performance; and iv) despite Machine and Deep Learning (ML/DL) techniques have gained enormous importance for the last years, they have not yet been widely explored in the individual device identification field [4].

In order to improve the previous challenges, the main contributions of the present work are:

- The definition of a general set of properties that should be fulfilled by any fingerprinting solution in charge of identifying identical single-board devices.
- The first ML/DL-oriented methodology that relies on behavioral fingerprinting to identify identical single-board devices, to the best of our knowledge. The proposed
methodology creates unique device behavioral fingerprints measuring the impact that insignificant hardware differences, happened during the manufacturing process of twin devices, have on the device performance when a given task is executed.

- The validation of the proposed methodology, as a Proof-of-Concept (PoC) available on [5], in a scenario composed of several identical Raspberry Pi 3 and 4 devices as those used in IoT scenarios. After testing different ML/DL algorithms, 92.6% average accuracy was achieved by Random Forest, and a perfect identification was carried out by setting a 50% threshold in the assigned classes.

- A detailed analysis of existing device fingerprinting solutions for individual device identification, analyzing their suitability for IoT environments with single-board devices. This analysis includes the comparison of these solutions with the proposed methodology.

The remainder of the paper is organized as follows. Section II reviews the main solutions for identical device identification and discusses why these approaches are not appropriate for IoT environments based on single-board devices. Section III details the set of properties required in a fingerprinting solution to make it appropriate for individual device identification. The design of the proposed device identification methodology is explained in Section IV, verifying how each fingerprint property is accomplished. Section V acts as validation of the present methodology, implementing it as a PoC that verifies its applicability in a realistic use case. Section VI compares the literature works with the proposed methodology and depicts several lessons learned and limitations. Finally, Section VII shows the conclusions extracted from the present work and future steps in the research.

II. RELATED WORK

This section gives the main insights of the related work dealing with unique device identification, with particular attention to device identification without additional external hardware requirements.

As a main remark, it is worth mentioning that, to the best of our knowledge, there is no methodology for individual fingerprinting of IoT devices based on hardware characteristics. In fact, the same happens in the field of traditional devices such as personal computers. In this regard, the closest work is the one proposed by Babun et al. [16], in which a fingerprinting framework for identifying classes of Cyber-Physical Systems ( CPSs) was presented. This solution employed hardware and OS/kernel characteristics following a challenge/response mechanism for performance and system calls fingerprinting. During the validation, a set of single-board computers were employed. Nevertheless, the objective of this framework is device type (class) fingerprinting and identification, not individual device fingerprinting when hardware and software are identical. Therefore, following this approach, identical devices would generate the same fingerprints, as the data sources leveraged are based on OS/kernel or component-related data and do not seek to identify fabrication variations or imperfections.

Although not defined in the form of a methodology, it is essential to analyze existing work focused on individual device fingerprinting and identification for other types of devices, discussing why it is not appropriate for single-board devices. In this context, traditionally, Physical Unclonable Functions (PUFs) have been one of the main methods for unique device identification. PUFs are hardware elements that generate a unique physically-defined fingerprint for a given output based on the manufacturing characteristics of the physical chips. PUFs have been employed in IoT from several perspectives [17]. However, PUFs require additional dedicated hardware elements that have to be attached to the device, making this solution not scalable in large environments or where direct access to the device is not possible. In addition, it increases the cost of the deployments. From crystal oscillator analysis, Salo [6] exploited differences in Real-Time Clocks (RTCs) and sound card Digital Signal Processors (DSPs) based on the drift between these chips and the CPU cycle counter (TSC in Intel processors). RTC-based and DSP-based differentiation achieved 98.7% and 93.3% of uniqueness when 703 computer pairs were evaluated. However, this method involves the use of components that, although common in computers, are not often available in single-board devices. Also leveraging oscillators, Sanchez-Rola et al. [12] proposed a fingerprinting method based on execution time. The authors cyclically executed a simple function to generate a time matrix, and then they calculated the statistical mode of each matrix row to generate the fingerprint. Then, matching values in the fingerprints were compared according to a similarity threshold. The authors were able to identify two computer sets of 176 and 89 devices, and achieved 85% on a web-based implementation. Compared to this work, single-board devices do not include an RTC with which to compare CPU time (two different clocks are required to analyze their deviation). Furthermore, after experimenting with this approach on single-board devices, it has been found that the resolution when measuring time on single-board devices does not allow this solution to be applied.

Additionally, some works have addressed identical device identification based on clock-skew calculated from network packets [18], [8], [10] or wireless beacons [17]. However, they have shown scalability issues when the number of devices increases and require a common observer in the fingerprint and identification process; if the observer changes, the identification is no longer possible [19], [19], [3]. Besides, raw radio frequency measurements [13], [14] and Bluetooth transmissions [20] have also been used to identify devices uniquely, but these methods, as other wireless-based methods, require a near physical location to the fingerprinted device.

Based on hardware performance behavior, Wang et al. [9] analyzed the differences that occur when writing a page in a Flash chip based on manufacturing variations. To evaluate different fingerprints of the same page, the authors used Pearson correlation coefficient. Based on their experiments on 24 chips, the authors showed an estimated false positive chance of $4.52 \times 10^{-5.15}$, and a false negative chance of $2.65 \times 10^{-5.39}$. However, not every device includes a Flash chip to apply the technique and its usage requires knowledge of low-level hardware. Recently, Dong et al. [15] developed a fingerprinting
works. After reviewing these related works, the following
input/output, and other components are integrated into a single
to consider. The main one is that all processing, memory,
computers, there are essential differentiating characteristics
of applications and operating systems, very similar to traditional
computers, many processing components integrated into a System
on a Chip (SoC). SoCs integrate microcontrollers with
more advanced processing units such as CPUs, GPUs,
or memory circuits in a single chip. As each of these
components uses a different frequency to operate, it is
common to use Phase-Locked Loops (PLLs) in the SoC
(circuit board. This integration brings the following special
aspects to consider:

- **Reduced number of crystal oscillators.** Due to the
objective of reducing costs, single-board computers usually
dispensable with components that are not critical. Thus,
machines eliminate the RTC and other physical
oscillators, simulating their presence through software
or using another oscillator as source frequency. The most
common is to have only one or two oscillators, one for
the base frequency of the processing components and another
for USB and network interfaces.

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for USB and network interfaces.

- **Constrained processing power.** Although single-board
computers offer increasingly higher computing capabilities,
they also aim to maintain low resource consumption and
low price. For these reasons, the performance of single-
board computers is not comparable to that of today’s
computers or servers. This is important and should be
taken into account when generating the fingerprint.

### III. IDENTICAL IDENTIFICATION IN IoT SCENARIOS: DEVICES AND PROPERTIES

This section presents the peculiarities of single-board devices
commonly used in IoT environments, as well as the properties
that identification solutions based on behavioral fingerprinting
should meet in the context of IoT.

#### A. Single-Board Device Description

Although single-board devices offer great flexibility in terms
of applications and operating systems, very similar to traditional
computers, there are essential differentiating characteristics
to consider. The main one is that all processing, memory,
input/output, and other components are integrated into a single

#### TABLE I: Individual device identification solutions based on device behavior fingerprinting.

| Work | Year | Device Type | Algorithms | Behavior | Features | Results |
|------|------|-------------|------------|----------|----------|---------|
| 6    | 2007 | General computers | Statistical | Processors and oscillators |RTC and DSP drift compared to the TSC | 98.5% and 93.3% of differentiation by RTC and DSP in 38 PCs, respectively. |
| 7    | 2009 | Wireless access points | Expectation Maximization | Clock skew | Wi-Fi beacons timestamps | Clock skew is a robust method and can detect different LAN APs. |
| 8    | 2012 | General computers | Statistical | Clock skew | TCP and ICMP timestamp | Both identical and different devices correctly identified. |
| 9    | 2012 | General computers | Correlation coefficient | Flash memory | Bit partial programming | Estimated false positive chance of $4.52 \times 10^{-11}$, and a false negative chance of $2.65 \times 10^{-5}$. |
| 10   | 2014 | Wireless devices | ANN | Clock skew + Network | Communication skew and patterns | From 99 to 95% accuracy and 74% recall on individual classification. |
| 11   | 2015 | General computers | Entropy | GPU | Frames per second | Graphic rendering show differentiation capabilities on 9 identical PCs, but no advanced tests were performed. |
| 12   | 2018 | General computers | Statistical (Mode) | System processors | Matrix of code execution times | 100% host-based and +80% web-based device identification in two sets of 89 and 176 PCs. |
| 13   | 2018 | Wireless devices |MLP, CNN, LSTM | Electromagnetic signals | Radio frequency | 96.3% accuracy for MLP, 94.7% for CNN and 75% for LSTM when identifying 6 identical ZigBee devices. |
| 14   | 2018 | Wireless devices | CNN | Electromagnetic signals | Raw frequency | 98% accuracy is achieved when identifying 5 identical devices. |
| 15   | 2019 | General computers | Dynamic Time Warping | Resource usage | CPU usage-based graph | 93.43% of uniqueness in the generated fingerprints of 10 identical devices. |
| 16   | 2021 | CPUs | Correlation-based (Own) | Hardware and OS/kernel | Syscalls, Memory, CPU, Time | Device type (model/OS version) identification, not individual identification. |
Uniqueness. An efficient fingerprinting method should be able to uniquely identify its associated device. In other words, a fingerprint should not be generated by two different devices.

Stability. The fingerprint generated by a device should be consistent in time. It means that a new fingerprint of a given device should be similar enough to the previous ones of the same device.

Diversity. The data sources and data format used to generate the fingerprint should be varied enough, so different devices generate different fingerprints. This characteristic is intrinsically related to stability, as increasing too much fingerprint diversity can affect its stability, and vice versa.

Scalability. The fingerprint should continue being unique as the number of devices to be identified increases. This can be achieved by adding additional features to the fingerprint or by looking for features that ensure uniqueness. Thus, this characteristic is very closely related to the uniqueness property discussed before.

Efficiency. To have a fingerprint useful for a live identification process, the generation and evaluation should not consume excessive resources, either in processing power or time.

Robustness. The generation of the fingerprint must be immune to changes in the context that may affect the data used in the fingerprinting process. These changes in the context may include elements such as temperature, time synchronization, or resource exhaustion, among others.

Security. The fingerprint should be secure to tackle device unauthorized access or adversarial attacks. This property implies a complete fingerprint life cycle, from its generation to storage and comparison in future identification processes.

IV. METHODOLOGY DEFINITION

This section describes a novel ML/DL-oriented methodology to identify identical single-board devices using behavioral fingerprints. It focuses on measuring the impact that insignificant hardware differences, which happened during the device manufacturing process, have on the device performance to create unique and stable behavior fingerprints. These differences are recognized by analyzing the performance of several components, according to parameters such as execution time or number of cycles. Thus, it is worth noting that this methodology could be applied to other types of devices containing at least two components to compare their behavior.

As shown in Fig. 1 the proposed methodology follows a client/server model and is composed of two fundamental phases: a first one of generation and a second of evaluation. During the fingerprint generation phase, the objective is the creation of a fingerprint per device by training ML/DL models for later device identification. During the fingerprint evaluation phase, new fingerprints per device are generated to be evaluated with the ML/DL models trained in the previous phase, giving a final identification output for the device. These two phases, and thus the methodology, consist of the next seven fundamental steps, which can be repeated in both phases depending on the tasks to be carried out:

- (A) **Hardware Component Selection.** Select the device components whose behavior is going to be analyzed.
- (B) **Component Isolation and Stability Assurance.** Implant stable conditions for the components, reducing external inferences to a minimum.
- (C) **Data Gathering.** Measure the behavior of device hardware components.
- (D) **Data Preprocessing and Feature Extraction.** Remove erroneous measurements, normalizes them, and extracts new significant values.
- (E) **Evaluation Approach Selection.** Decide between classification or anomaly detection depending on the environment properties.
- (F) **Model Generation and Evaluation Design.** Train ML/DL algorithms, select performance metrics, and establish model thresholds.
- (G) **Device Evaluation and Identification Decision.** Repeat steps B, C, and D to perform device identification.

Fig. 2 shows the relationship between the different steps...
detailed above and the properties desired in an individual device identification solution, as introduced in Section III-B.

A. Hardware Component Selection

The first step is to analyze the hardware of the device where the fingerprint needs to be generated. The goal is to identify components with potential manufacturing variations whose performance can be accurately measured and compared.

In this sense, since the fingerprint will be based on device self-contained hardware, it is necessary to identify at least two components to be used, as their behavioral performance will be compared to each other, although to improve the scalability and diversity of the fingerprint more could be added if available. The preference here is to select components whose frequency is based on different physical oscillators, as their differences will be larger, although components with different frequencies sharing one oscillator as the base frequency can also be compared. Examples of components to consider in single-board devices: CPU, GPU, memory, network controllers, USB controllers, or time control oscillators.

B. Component Isolation and Stability Assurance

Once the hardware components to be monitored are chosen, the next step is to establish a configuration that ensures the stability of the behavioral measurements. This step seeks to ensure a stable and identical condition during the generation of the fingerprint, both for training and testing phases. At this point, it is critical to guarantee that there are no external elements introducing noise or variability.

With that goal in mind, one of the key factors to take into account is the frequency at which the component is operating, since in single-board computers it is common for the operating system to establish some adaptability according to the load on the system or the need to save energy. Thus, it is necessary to ensure that the fingerprint will be generated under identical frequency conditions. Otherwise, it would be impossible to compare the variation in performance between various components. In this sense, components such as the CPU or GPU are the ones that can have more variability in their operating frequency, ranging from some MHz when are in power-save mode to several GHz when they are under high-performance requirements. Another aspect to take into account is the isolation of the software that performs the measurements with respect to other programs running on the system. The measures to guarantee this isolation include the separation of some of the CPU cores from the general process scheduler, the use of transactional memory [22], the disabling of interrupts by the kernel or isolating the GPU. Note that the exact actions may vary according to the components chosen. Moreover, it is also important to control external conditions such as temperature to the extent possible, since it can influence the performance variation of some components. In the case of using CPU timers, time synchronization made by services such as NTP should be also considered. These considerations seek to improve the robustness of the fingerprinting solution.

C. Data Gathering

When the desired stability conditions have been achieved, it is necessary to define the functions to be performed on the components (selected in phase A) to measure their behavior in parallel and determine the possible skew between them. In this sense, the measurements must allow the comparison of the performance of two different components from the same device, avoiding executing the operations and measuring the deviation using a unique component.

Choosing the functions to run on each component to compare their behavior is a critical task during the fingerprinting solution design and must be carefully studied to ensure the efficiency, diversity, and uniqueness of the fingerprint. Due to the fact that functions taking longer times to execute may better show the variance between components, but may make the fingerprint generation process take too long. In addition, the created approach should not consume too many resources as it could slow down the normal operation of the system and affect other tasks. For example, the authors of [12] decided to measure functions that take a short time to execute using the RTC, comparing CPU, and RTC oscillators. Besides, the authors of [6] measured the clock cycles in one second compared with the RTC and when processing one second of audio using the DSP. Finally, this step sends the generated behavioral data to a server, where it will be processed to generate the fingerprint. This sending should be done over a secure communications channel, such as SSH or TLS, to avoid possible interceptions of data transmissions affecting the fingerprint security. Also, another measure to be considered is the use of Trusted Execution Environments (TEEs) [23], if available, to isolate the fingerprint generation task from the rest of the device processes.

D. Data Preprocessing and Feature Extraction

Once the server receives the behavioral data, the next step is to preprocess the data to eliminate possible erroneous measurements and extract new information. Here, note that the
E. Evaluation Approach Selection

Once the features that will generate the fingerprint have been obtained, it is necessary to define the ML/DL approach to be followed [24]. There are two possibilities here, a classification approach, in which the different devices in the environment will be associated with a label, and an anomaly detection approach, where the data from each device is labeled as “normal” and a separate model is generated for each of them.

This decision must be made taking into account both the scenario (number of devices, variety of devices, possibility of adding or removing devices) and the features that have been collected (similarity of values between devices, number of features, etc.). Thus, an environment with a low number of devices may benefit from the use of classification algorithms, while more dynamic environments with a large number of devices will need more varied features and will benefit from anomaly detection algorithms. Here, the scalability and efficiency of the approach are better if no retraining is needed each time a device joins or leaves the scenario. In the literature, solutions have been found with both approaches, applying classification perspectives [16] or generating a statistical model per device and confronting the new fingerprints to it when identification is to be performed [12].

F. Model Generation and Evaluation Design

Once the desired approach has been selected, either classification or anomaly detection, it is necessary to train ML/DL algorithms and define the metrics that will be used in the identification. This step should be carried out considering the efficiency in the evaluation process and the security against possible data-based attacks to the models.

There is a wide variety of algorithms that can be considered in this step, differentiating between traditional ML algorithms and DL algorithms based on neural networks [24]. Starting from classification, algorithms such as Random Forest, k-Nearest Neighbors, xXtreme-Gradient Boosting (XGBoost), Support Vector Machines (SVM), or Multi-Layer Perceptron (MLP) can be used. From the anomaly detection prism, Isolation Forest, Local Outlier Factor (LOF), One Class-SVM, or Autoencoders are good alternatives as well. At this stage, it is also worth considering the application of algorithms focused on time series [24], depending on whether there are time-based dependencies between the values. Once the algorithms to use have been selected, it will be necessary to train and fine-tune the hyperparameters that give the best results in each of them. Note that these hyperparameters will vary according to the selected algorithms. In addition, the model predictions are usually one per vector, so they cannot be used directly to give a decision during the evaluation and identification of the device. In this sense, it is common to determine a threshold based on the model performance from which the device under evaluation will be accepted as the legitimate one. This threshold can be defined using numerous equations or conditions, such as defining the 50% of the values being recognized as legitimate, as done by the authors in [12]. Common metrics to consider on this step are accuracy, true positive rate (TPR), false positive rate (FPR), or F1-Score, among others [24].

At this point, it is worth noting that although this methodology has been designed primarily for ML/DL algorithms due to their current prominence in many research fields, it could be possible to include in this step other statistical algorithms, or even some self-developed algorithms as in [16].

G. Device Evaluation and Identification Decision

This step is only carried out in the evaluation phase and involves generating new behavioral data of the device following the same methodology as during the training phase, repeating steps B, C, and D.

Once the new dataset is generated, it is used to identify the device, determining whether it is the same device used during training or not. To this end, data will be evaluated using the ML/DL models previously generated, so that one result per vector is obtained. Then, the rule determined in the previous step will be applied, either based on a threshold or another equation to give a final decision on the device identification.

V. METHODOLOGY VALIDATION

This section validates the suitability of the proposed methodology by implementing a Proof-of-Concept (PoC) on a realistic scenario composed of 20 identical single-board devices. In particular, the devices are 10 Raspberry Pi 4 Model B 2GB...
(RPi 4) and 10 Raspberry Pi 3 Model B+ (RPi3) running identical software images, with Raspbian 10 (buster) as OS and 5.4.83 as Linux kernel version. The operating systems run in headless mode, i.e., without a graphical environment or output to a display, a common configuration in SOC devices deployed in IoT. Next, it is detailed how the methodology has been implemented in the previous scenario, describing the decisions made in each of the defined steps. The language used has been Python and the code is available in [5], for reproducibility sake.

A. Hardware Component Selection. As a starting point, the physical oscillators available in the RPi4 and RPi3 were analyzed. The result of this study concluded that one oscillator is shared between the SoC components, running at 54 MHz in RPi4 and 19.2 MHz in RPi3, and the USB controller running at 25 MHz in both models [25]. Since accessing the frequency of the USB oscillator from the device is not simple, the selected components were the VideoCore VI GPU and the ARM Quad-core Cortex-A72 CPU for RPi4 and VideoCoreIV GPU and the ARM Quad-core Cortex-A53 for RPi3. Although they share the base oscillator (GPU and CPU), their frequencies are given by different PLLs.

B. Component Isolation and Stability Assurance. Both the CPU and GPU work at varying frequencies depending on the load on the device. So, to guarantee the stability of the signatures, it is needed to ensure that frequency is fixed. For the validation, the RPi4 CPU frequency was set to 1.5 GHz and the GPU one to 500 MHz, while the RPi3 CPU frequency was set to 1.4 GHz and the GPU one to 400 MHz, the maximum values of both by default (without overclock). To do this, the Turbo Mode was enabled by adding force_turbo=1 in /boot/config.txt. After that, one of the CPU cores was isolated to be used in the fingerprint generation, making use of the options in the /boot/cmdline.txt file, preventing processes from being assigned to it.

C. Data Gathering. To measure the variation of behavior between components, it was compared how the cycle counters of each component (CPU and GPU) vary with respect to the other. To do this, sleep, random number generation, and hash functions were selected. In particular, these functions were sequentially executed in the CPU and the number of GPU cycles that occurred during each function execution was measured. To interact with the GPU, Idein’s py-videocore6 library [26] was used in RPi4. Concretely, the CORE_PCTR_CYCLE_COUNT GPU counter was the register monitored. In the case of RPi3, Idein’s py-videocore [27] library was used to monitor the QPU_Total_idle_clock counter (as the RPi3s were in headless mode). The data gathering procedure is summarized in Algorithm 1. For the data collection, the sleep function time \( t \) was set to 120 seconds, as the variations between CPU and GPU are presumably low, a fixed string was set for the hash function, and the number on measurements \( n \) was set to 400. It is important mentioning that these values were adjusted according to the results in later steps. Other configuration parameters such as \( t=60 \) seconds were tested providing with slightly worse results.

D. Data Preprocessing and Feature Extraction. The data gathering process was repeated a total of ten times per device, for testing purposes, with different temperature conditions and performing several reboots between the generation of each fingerprint (set of measurements). Then, the 400 measurements of each fingerprint were grouped in different sliding windows ranging from 10 to 100 values in jumps of 10 values (10 different sliding windows in total). Afterwards, several statistical features were calculated for each window-based group and concatenated together. Concretely, the statistical values calculated were: minimum, maximum, mean, median and sum. Following this approach, the resultant vectors for training and evaluation have a size of 150 (3 data gathering functions * 10 different sliding windows * 5 statistical features).

E. Evaluation Approach Selection. Due to the staticity of the test environment, as the number of devices do not change in time, it was decided to follow an approach based on classification ML algorithms combined with a threshold that would delimit the minimum number of successfully classified vectors.

F. Model Generation and Evaluation Design. For the model generation, six fingerprints of each device were used as separate training in order to have cross-validation. The selected algorithms were Random Forest, Decision Tree, k-NN, XGBoost, Naive Bayes, and SVM. After hyperparameter optimization (see TABLE II), using cross-validation with the fingerprints used for training, the best performing algorithm was Random Forest (number_of_trees=100, max_depth=None, min_samples_split=2), giving an average accuracy of 92.61%, ranging from 100% in the best case to 70% in the worst (a random predictor would give 10% for each device, as the model can be easily identified based on device frequency). Fig. 3 shows the results per algorithm and device. This value varies highly, as some of them seem to be more similar between them. Based on the previous results, a threshold of 50% in the assigned classes in evaluation can be defined to give the identification decision, so that if half of the vectors are correctly classified in the assigned classes in evaluation can be defined to give the identification decision, so that if half of the vectors are correctly classified, the fingerprint is considered valid.

Algorithm 1: CPU/GPU data acquisition algorithm

```
Result: Set of GPU/CPU performance measurements. result_set={};
for n in n_measurements do
    #Sleep cycle counter
    sleep_time=CPU_CYCLE_COUNT=0;
    sleep(t);
    sleep_cpu_cycles=CPU_CYCLE_COUNT;
    #Random number generator cycle counter
    random_number_gen();
    random_cpu_cycles=CPU_CYCLE_COUNT;
    #Hash cycle counter
    hash_gpu_cycles=GPU_CYCLE_COUNT=0;
    hash("Test string");
    hash_cpu_cycles=GPU_CYCLE_COUNT;
    #Add measurements to result set
    result_set.append("sleep_cpu_cycles,
                    random_cpu_cycles,hash_cpu_cycles");
end
```

For each device, the algorithm was trained with all the measurements from the other devices as input and the result was then compared to the measurements of the device under evaluation, computing a set of performance metrics. The resulted vectors were then evaluated in the best performing algorithm. 

The accuracy of the algorithm was calculated using the formula:

\[
\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}} \times 100
\]

Where Correct Predictions is the number of times the algorithm correctly predicted the device, and Total Predictions is the total number of predictions made. The algorithm was then compared against the other algorithms and the features were analyzed to identify patterns and trends.

The performance of the algorithm was evaluated using the following metrics:

- **Accuracy**: the percentage of correct predictions made by the algorithm.
- **Precision**: the percentage of correctly predicted devices among all devices predicted as that type.
- **Recall**: the percentage of correctly predicted devices among all devices that were actually that type.
- **F1 Score**: the harmonic mean of precision and recall.
- **Cross-Validation**: the algorithm was evaluated using cross-validation to ensure that the results were not biased.

Finally, the algorithm was deployed in IoT, using the fingerprints generated from the data gathering process, and was tested in different environments to ensure its robustness and reliability.
TABLE II: Classification algorithms and hyperparameters tested.

| Algorithm     | Hyperparameters tested                                                                 | Avg accuracy |
|---------------|----------------------------------------------------------------------------------------|--------------|
| Naive Bayes   | No hyperparameter tuning required                                                      | 85.34%       |
| k-NN          | $k \in [3, 20]$                                                                        | 70.39%       |
| SVM           | $C \in [0.01, 100]$, $gamma \in [0.001, 10]$, $kernel \in \{\text{rbf'}, \text{linear'}, \text{sigmoid'}\}$ | 86.35%       |
| XGBoost       | $lr \in [0.01, 0.30]$, $max\_depth \in [3, 15]$, $min\_child\_weight \in [1, 7]$, $gamma \in [0, 0.5]$, $colsample\_bytree \in [0.3, 0.7]$ | 91.35%       |
| Decision Tree | $max\_depth \in [None, 5, 10, 15, 20]$, $min\_samples\_split \in [2, 3, 4, 5]$         | 87.71%       |
| Random Forest | $number\_of\_trees \in [50, 1000]$, $max\_depth \in [None, 5, 10, 15, 20]$, $min\_samples\_split \in [2, 3, 4, 5]$ | 92.61%       |

G. Device Evaluation and Identification Decision. In the present PoC, this phase was performed with the four fingerprints of each device not used for the previous phase. In this step, the normalization was repeated with the same values used to generate the model, and the vectors containing the same features were evaluated using the Random Forest model trained previously. Using the 50% threshold as explained above, all the devices were correctly identified without any device erroneously identified as another one. Fig. 4 shows the average confusion matrix for the four fingerprints used for testing, using Random Forest as classifier. The labels are defined as the device model followed by its MAC address. The evaluation is done by grouping together devices within the same model, as RPi3 and RPi4 have different running frequencies in the components leveraged and they can be easily differentiated.

As conclusion, it has been demonstrated the possibility of applying the proposed methodology in an environment with real devices in a satisfactory way. Still, this is only a PoC and its performance could be substantially improved by extracting other data from devices and generating more elaborate features.

VI. DISCUSSION

This section compares the proposed methodology with the solutions available in the literature. After that, it discusses the limitations of the proposed solution and provides some lessons learned.

A. Literature comparison

Despite the solutions discussed in Section II do not follow a common methodology, many of them implement certain steps of the one proposed in this work. Therefore, TABLE III makes a comparison between the proposed methodology and the related works that use on-device components for identification. As can be seen, all works performing identification utilize a threshold, defined based on different statistical approaches. Besides, none of the approaches employed ML/DL algorithms and many of them did not consider hardware isolation properly.

After the theoretical comparison, it is relevant to analyze the most similar and comparable solutions from a common prism. Although most of the solutions analyzed in Section II use components that are not available on the RPi4 or RPi3 of our scenario, two of the solutions, [15] and [11], can be adapted to our scenario and methodology. TABLE IV compares the methodology approach and the results of our validation with two implementations inspired in the works found in Section II.

The first of these approaches was inspired by [15], for which only the CPU was selected as a component but making the fingerprint of each of its cores separately by using thread affinity. The features to be obtained were statistics based on the time taken to perform small operations on each of the cores. Using LOF as an anomaly detection algorithm and one model per device, the identification was possible by setting a threshold of 50%. However, the reboot of the devices caused the fingerprints to change and it was not possible to perform the identification due to the new process scheduling made by the kernel, something that may also be affecting the proposed solution in [15]. The same problem occurred in a second tested approach inspired by [11]. In particular, each CPU core was compared with the GPU separately in a concurrent manner and executing short operations. Here, different operations of variable complexity were performed in the GPU while the...
execution time was measured using the CPU. In this case, the evaluation also followed an anomaly detection-based approach, being LOF the algorithm with the better results. Again, it was possible to identify the devices consistently, now using a threshold around 60%, until they are rebooted.

From these results, it can be inferred that, although the stability of these approaches is not sufficient, they would be useful in IoT environments where device reboots are not possible, such as in the control of electrical or security systems.

B. Lessons Learned and Limitations

From the above comparison and the tests performed, valuable conclusions are drawn, both in the form of lessons learned and possible limitations of the proposed methodology. Regarding lessons learned, the main ones are:

**Component isolation is critical.** From the above experiments, it can be seen that isolating the measurements from external processes is crucial to ensure the stability of the fingerprinting process.

**Rebooting can have impact on the fingerprints.** It is observed that the restart of the devices has an impact when the CPU core is not isolated from other processes, probably due to the effect of the process scheduler.

**Temperature does not seem to affect the components selected for validation.** The above tests have been performed at different temperature conditions and this does not seem to affect the results, possibly because by using integrated components on the same chip, it affects the base frequency and overall performance equally.

In terms of limitations of the methodology, the following have been identified:

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**TABLE III: Analogy between hardware-based fingerprinting solutions in the literature and the proposed methodology.**

| Work | Step A | Step B | Step C | Step D | Step E | Step F | Step G |
|------|--------|--------|--------|--------|--------|--------|--------|
| [10] RTC, DSP, CPU | - | CPU cycles in one second (measured with DSP and RTC) | Raw values | - | Statistical t-test, \( p < 0.05 \) threshold | 98.7%-93.3% identification |
| [12] RTL, CPU | Transactional memory | - | Execution time of short functions | Mode-based matrix | - | Statistical comparison, 50% similarity threshold | Correct identification |
| [9] Flash memory | Isolation of one page in flash memory | - | Bit programming errors (flip from 1 to 0) | Error order per bit | - | Pearson correlation, 0.5 threshold | Estimated 4.52 \times 10^{-8} FPR and 2.65 \times 10^{-5} FNR |
| [14] CPU | Thread affinity | - | CPU usage while executing a cyclical tasks | Raw values | - | Dynamic Time Warping algorithm, 0.3244 threshold | 93.43% uniqueness (Shannon entropy) |
| [11] CPU, GPU | Number of Frames per 5 seconds | - | Entropy and statistics | - | Statistical | No evaluation, partial differentiation capabilities |

**This work**

- CPU and GPU Core isolation, Fixed frequency
- Sleep for 120 secs, Random num. gen., hash
- Sliding window-based statistical features
- Classification
- Random Forest, 50% threshold
- Perfect Identification (92.6% avg. accuracy)

**TABLE IV: Comparison of the validation approaches implemented.**

| Approach | Step A | Step B | Step C | Step D | Step E | Step F | Step G |
|----------|--------|--------|--------|--------|--------|--------|--------|
| This work (Sec. 8) | CPU and GPU | Core isolation, Fixed frequency | Sleep for 120 secs, Random num. gen., hash | Sliding window-based statistical features | Classification | Random Forest, 50% threshold | Perfect Identification (92.6% avg. accuracy) |
| [13] inspired approach | CPU | Thread affinity | Short functions | Raw values | Anomaly Detection | LOF, 50% threshold | Identification until device reboots |
| [11] inspired approach | CPU and GPU | - | Different complexity GPU operations | Raw values | Anomaly Detection | LOF, 50% threshold | Identification until device reboots |
The methodology implementation is highly dependent on the hardware model. The implementation of the present methodology, being based on the hardware components available in the devices, is highly dependent on the libraries needed to interact with them. Thus, implementations of the methodology may not be compatible between different models of single-board devices if their components are different, so it would be necessary to adapt the code.

Some steps might need an exploratory analysis. It is difficult to determine which hardware behavior measurements to take or which features to extract a priori. So, the implementation of the methodology may require several exploratory iterations to find a combination that meets all the properties needed in the generated fingerprint.

VII. CONCLUSIONS AND FUTURE WORK

This paper proposes an ML/DL-oriented methodology composed of seven steps that allow identifying identical single-board devices (same hardware and software configuration) used in IoT scenarios. These seven steps are grouped into two main phases, one to generate the behavioral fingerprint and another to evaluate it and identify the device. This work also defines seven properties that solutions dealing with identical device identification based on behavioral fingerprint must consider. The proposed methodology has been successfully validated in a real environment composed of 20 identical Raspberry Pi 4 Model B and Raspberry Pi 3 Model B+, being able to perfectly identify them using a Random Forest model trained using features derived from the variation in performance between their CPU and GPU by setting a 50% accuracy threshold. Besides, this work compared the methodology identification performance with other implementations inspired in the literature works and provided some lessons learned and limitations.

As future work, we plan mainly to validate our methodology in larger scenarios with more devices and types, defining new features to be obtained and other ML/DL algorithms to evaluate the scalability of the solution in larger environment. Furthermore, it is desired to explore the use of TEEs when generating the fingerprint, guaranteeing the security of the measurements by isolating the fingerprinting program from the rest of the system processes.

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