Towards Reliable and Scalable Linux Kernel CVE Attribution in Automated Static Firmware Analyses

René Helmke and Johannes vom Dorp
Fraunhofer FKIE, Bonn, Germany, Email: {rene.helmke, johannes.vom.dorp}@fkie.fraunhofer.de

Abstract—In vulnerability assessments, software component-based CVE attribution is a common method to identify possibly vulnerable systems at scale. However, such version-centric approaches yield high false-positive rates for binary distributed Linux kernels in firmware images. Not filtering included vulnerable components is a reason for unreliable matching, as heterogeneous hardware properties, modularity, and numerous development streams result in a plethora of vendor-customized builds. To make a step towards increased result reliability while retaining scalability of the analysis method, we enrich version-based CVE matching with kernel-specific build data from binary images using automated static firmware analysis. We open source an attribution pipeline that gathers kernel configuration and target architecture to dry build the present kernel version and filter CVEs based on affected file references in record descriptions. In a case study with 127 router firmware images, we show that in comparison to naive version matching, our approach identifies 68% of all version CVE matches as false-positives and reliably removes them from the result set. For 12% of all matches it provides additional evidence of issue applicability. For 19.4%, our approach does not improve reliability because required file references in CVEs are missing.

I. INTRODUCTION

Safety, security, and privacy threats arise alongside embedded system markets. Growing device numbers inflate attack surfaces, raising impact and scope of newly found software vulnerabilities in domains pivotal to society [1]–[4]. Thus, it is important to maintain the software security of these systems.

Embedded devices boot into firmware: lightweight software packages tailored to the device’s use case and limited resources [5]. Similar to general purpose operating systems, they consolidate services, drivers, and interfaces, but in contrast are highly specialized towards their purpose. Minimizing costs, vendors commonly rely on Software Development Kits (SDKs), which make heavy use of open source. This gives the advantage of large development communities quickly providing patches when security issues arise.

Linux serves as configurable, modifiable, slim, and powerful system layer in many firmware images [6], [7]. It is open source, modular, and supports flavors of the MIPS and ARM Instruction Set Architectures (ISAs) commonly used in embedded devices. Vendors configure kernel builds to include all required functions, remove unused components, and add custom functionality. The compiled kernel is then distributed in binary form as part of the firmware.

As of 2022, there are over 2,900 Common Vulnerabilities and Exposures (CVE) documenting security issues of varying severity affecting different Linux kernel versions [8]. Yet, the firmware of various widely spread devices contains obsolete or end of life kernels [6], [7]. This raises questions about device exploitability regarding well-known vulnerabilities.

Intuitively, reproducible exploitation of the target provides undeniable proof for CVE attribution. However, science has yet to find scalable and effective methods for such dynamic verification in binary analysis [9], [10]. Heterogeneous system properties require custom solutions: For example, exploit code may be unavailable for the target ISA [10]. Resource constraints and missing build chains pose further challenges, as devices might be the only testing platforms available [9]. Emulation and re-hosting are options, but require substantial efforts to establish device compatibility [9], [11], [12].

Static analysis serves heuristics to find imperfect proof for CVE attribution, e.g., verifying code presence [13]. However, many approaches do not scale well as they require considerable manual work and deep knowledge of each CVE [10]. Parts are automatable, but needed data may be unavailable or incorrect in repositories [14], [15]. Also, automation becomes increasingly challenging in lights of proprietary formats, obfuscation, compiler optimizations, and symbol stripping [5], [10].

In lack of applicable methods, large-scale approaches like firmware analysis tools [16]–[18] and studies [6], [7], [19] commonly attribute bugs by matching versions against CVE databases. Trading in reliability for applicability, their results need manual verification but may raise awareness for potential security issues.

In 2020, we used version matching as part of a large-scale empirical study on home router security [7]. For the Linux kernel, this method proves exceptionally unreliable: Due to custom build configurations, we can not assume that kernels include components flagged as vulnerable for the subject version. E.g., CVEs affecting hardware drivers that vendors removed from their builds are not applicable, but the method does not cover this factor – leading to false-positive matches.

Qualitative evaluation of our approach showed high false-positive rates as build customizations for a control group of firmware samples were taken into account. While the large result set might still be useful for analysts, more precise methods are needed to reduce manual verification efforts [10].

To improve the reliability of version-based Linux CVE attribution in large-scale scenarios, we enrich the process with kernel-specific data from automated static firmware analysis. We extract kernel configurations from binary images and reconstruct the kernel build process to identify included com-

1https://iot-analytics.com/number-connected-iot-devices/, Accessed: 2022-09-05.
ponents with file-level granularity. Hereby, we reduce the set of false-positive matches requiring further manual verification.

In the following, we provide:

1) A description of our methodology for Linux CVE attribution, based solely on binary kernel representations.
2) An empirical evaluation in which we compare our approach against naive version-based CVE matching using the 2020 Home Router Security Report [7] dataset.

Furthermore, we release the implementation of the methodology used for the evaluation as open source to the public\(^2\).

II. BACKGROUND & RELATED WORK

There are various automation approaches to discover and attribute security issues in binary targets. Aside from version-based matching against vulnerability repositories, they include code similarity and patch analysis [20], taint analysis and symbolic execution [21], fuzzing [22], and various emulation-based methods [9]. While we acknowledge substantial work done in these directions, we point out their limited applicability in large-scale analyses due to resource constraints, low emulation success rates, and missing bootstrap data [9], [10].

Focusing on large-scale attribution of known security issues in firmware, this section first discusses the scientific need for sound data as foundation of reliable bug attribution (II-A). Then, we present attribution methods applied in large-scale firmware security studies (II-B).

For comprehensive surveys on state-of-the-art research and the problem space, especially in terms of scalability and automation, we refer to Qasem et al. [10] and Wright et al. [9].

A. Sound Data as Foundation for Reliable Bug Attribution

Detail information on known vulnerabilities lays the foundation of reliable bug attribution [10]. The community-driven CVE catalog [8] is the largest data source and de facto standard for vulnerability identification. For each tracked issue, there is an identifier, description, and follow-up references. The derivative National Vulnerability Database (NVD) [23] adds data on severity and impact scores, but also lists affected products and their versions. The latter is encoded in an identification scheme, the Common Platform Enumeration (CPE) [23].

Records vary in information quantity and quality. E.g., Sanguino and Uetz [15] show that errors in CPE assignments, but also data inconsistencies harm soundness. Code similarity approaches like [5] exemplify that pivotal data can be missing or is hard to obtain, as they require access to ground truth embedded in commits and patches. If CVEs affect closed source projects, issuers will not share technical details on fixes in public. For open source, Tan et. al. [14] show that code collection remains challenging: Patches are unreferenced, not marked, incorrect, or hide in bug tracker discussions.

Thus, researchers construct small datasets of selected CVEs that their proposed techniques can ingest for evaluation [10]. For each CVE, this implies in-depth investigation, additional data aggregation, and technical bug knowledge, which limits the applicability of previously mentioned approaches for large-scale scenarios. The Vulncode-DB [24] addressed this issue and annotated CVE data with fine-granular technical information, but got discontinued due to bootstrapping problems.

As for Linux kernel CVEs, issuers embed references to bug locations in the project’s source tree in CVE short descriptions [8]. In combination with extracted build configurations from firmware, the proposal in this paper takes advantage of this observation to identify components built into the kernel.

The linuxkernelcves.org [25] project argues that for Linux’s many version streams, contributors, and distributors, there is inaccuracy in CPE data to precisely track affected versions. They crawl commit references in CVEs from Linux distribution sources, e.g., Ubuntu and Android bug trackers, to determine the first patch appearance in mainline kernels. However, while [25] host a regularly updated dataset, they stress that their CVE post-processing code has neither been evaluated nor published yet – result reliability is unknown.

B. Static Bug Attribution in Large-Scale Firmware Analyses

In 2014, Costin et al. [6] execute a quantitative study on embedded device security by analyzing 32,000 firmware images. They implement pattern-based heuristics and specify indicators of security malpractice in firmware images, e.g., hardcoded passwords, cryptographic material, but also included application version numbers to attribute CVEs. Their static analysis yields CVE matches in userspace applications of 693 firmware images. While they inspect Linux kernel versions, these are not included in the bug attribution. Furthermore, [6] report unsolved challenges in result verification, as not only CVE data is incomplete, but also vendors may custom-patch affected files. Since 2014, cross-architecture code similarity methods have drastically improved and may be used as imprecise measure for verification in this case, e.g., FirmUp [5]. However, acquiring and processing patches for thousands of CVEs to bootstrap code similarity methods deems infeasible based on the imprecise CVE repositories.

Zhao et al. [19] develop FirmSec, a large-scale static analysis pipeline to empirically study vulnerabilities introduced by third-party components and software in IoT devices. Here, a novelty is that they identify software versions by extracting syntactical and control-flow graph features. They construct a repository of 1,191 third party components and then extract matching features out of the component’s corresponding source files. However, they neither consider vendor-specific build configurations nor the Linux kernel.

Similar to [6], we assess and compare the state of firmware security of 127 home routers available on German markets in our whitepaper Home Router Security Report 2020 [7]. Using the automated Firmware Analysis and Comparison Tool (FACT) [16], we also implement pattern-based heuristics to detect best practice violations in firmware images. E.g., we analyze the usage of exploit mitigation techniques like stack canaries and non-executable bits in userspace binaries. To quantize the differences between used Linux kernels in

\(^2\)https://github.com/fkie-cad/cve-attribution-s2. Accessed: 2022-09-05.
III. METHODOLOGY

This section describes our proposed methodology to enrich the version-based Linux kernel CVE attribution process with build-specific annotations. We show an automated static analysis pipeline that finds and extracts kernel configurations, dry builds the found kernel version, and filters CVEs based on affected version and build log-included files.

Figure 1 provides an overview of our methodology. We establish a two-stage process: In the first and left-hand stage, we unpack, analyze, and annotate each file of an ingress firmware image. Gathered information includes Linux kernel version, ISA, and kernel build configuration. In the second and right-hand stage, we leverage upon said data to perform the actual CVE attribution and filtering step. Yellow boxes in Figure 1 mark components this paper contributes.

In the two following subsections III-A and III-B, we provide detailed technical insights on each stage and step. We finish with a short example of CVE-2017-17864 in III-C to demonstrate the added attribution reliability our approach offers.

A. Gather Kernel Information via Static Firmware Analysis

For stage one, we apply and enhance the firmware analysis tool FACT [16], which is maintained at our research group. FACT is open source, comes with a variety of firmware container unpackers, and provides a plugin system with ready-to-use analysis modules we can leverage for kernel version and ISA detection. In the following, we describe all pipeline steps that are of importance for the proposed attribution methodology.

Consider an arbitrary firmware image. After submitting it to the pipeline, FACT’s Unpack Scheduler tries to identify container formats. Choosing from a palette of custom extractors and integrated tools like binwalk [26], it recursively extracts or decompresses file contents until all options are exhausted.

The Analysis Scheduler receives each extracted file and applies a preconfigured set of analysis plugins. These implement heuristics, e.g., based on YARA [27] rules, third party tools like checksec [28], or custom analysis implementations. Analyzed files and their annotated results are stored in the Result Database & File Storage.

Our methodology depends on the results of three plugins: Software Components, Kernel Configuration, and Architecture Detection. While FACT already provides the former and latter, this paper contributes the new Kernel Configuration plugin.

The Software Components plugin applies YARA rules to detect various software components along with their version.
One of the rules, a part of which is shown in Listing 1, detects the Linux kernel and its version.

We contribute the Kernel Configuration plugin, which detects and extracts Linux kernel build information. Stage two of our pipeline requires this data to filter out CVEs applicable to components excluded from the build.

Figure 2 illustrates the plugin’s high-level control flow. Not explicitly stated edge transitions lead to analysis termination. Inside a firmware, kernel configurations may be present in different plain text and binary formats. Thus, depending on the file’s MIME type, the plugin differentiates between kernel-related binary files and plain text. Here, plain text is the most straightforward case, as the plugin then checks for headers and build configuration directives. An example plain text configuration can be found in the Debian Repositories.

Another way to obtain the configuration is by making use of an enabled CONFIG_IKCONFIG directive: When it is set to Y during the firmware kernel’s build time, a copy of the configuration is embedded into the binary image – either as inline string or compressed container. If it is set to M, said information is outsourced to a kernel module. Thus, if the file is either a kernel image or module, our plugin searches for a magic word that is prepended to the inline string. Once found, we apply a set of signatures to detect the correct format of the embedded configuration and annotate our findings to the analyzed file. Otherwise, we seek for embedded containers, try to extract them, and again check for magic word and format.

The Architecture Detection plugin identifies target ISAs using four different measures. For executable files in ELF format, it parses the e_machine and e_flags fields of the file header. For kernel configurations, it searches for the presence of architecture-specific feature directives. E.g., ARM64_USE_LSE_ATOMICS is only supported by the ARMv8 specification. Furthermore, the plugin detects and parses CPU information from device trees [29] – a widely spread bootloader-to-operating-system interface which also lists system hardware and its properties. Finally, the plugin does also rely on MIME databases to identify any file type that might leak target platform information.

B. Build Log-assisted CVE Attribution

The build log-assisted CVE attribution is the second stage of our proposed analysis pipeline in Figure 1. Here, we first use FACT’s REST API to consolidate the kernel version, kernel build configuration, and detected target ISA.

Then, the Kernel Downloader fetches version sources from kernel.org. Note that the assumption of vendors using a mainline, i.e., unmodified, kernel is false in general due to custom patching and additional proprietary components. Large parts of Linux are licensed under the GNU General Public License (GPL) and, thus, modifications must be published. However, for two reasons we could not find a scalable way to obtain these versions: First, some vendors distribute packages through individual processes on request. Second, the required build tools do not have to be part of the package – which is pivotal to our pipeline.

Dry Build is the next step in Figure 1: We set the target ISA and install the extracted kernel build configuration in the downloaded kernel source code. Then, we execute a dry run via make, which does not compile the kernel but prints each compilation recipe instead. This approach has the advantage of low computational overhead and does not require cross-compilation environment bootstrapping. The goal of this step is to gather a list of source files from the build log, which our pipeline witnessed to be included in the kernel.

The CVE Fetcher executes simultaneously. Here, we query the NVD [23] dataset for all Linux kernel CVEs and filter out all records that do not refer to applicable CVEs is the output of version-based attribution.

Finally, the Filter step combines the outputs of CVE Fetcher and Dry Build: As we observed that Linux kernel CVEs state the affected source files in their short description, records from the version-based result set can be eliminated. We reduce it by removing every CVE that does not reference an affected file we witnessed in the build log.

C. Short Example - CVE-2017-17863

To demonstrate the practical addition of our Linux kernel CVE attribution pipeline, we shortly present an example using CVE-2017-17863. The record description states an invalid memory access due to an integer overflow in kernel/bpf/verifier.c. Also, CPE states that kernel versions from 4.9 to 4.9.71 are vulnerable.

Consider a firmware sample with Linux kernel 4.9.60 and the underlying kernel configuration. Naive version-based matching reports a positive match as the version is within CPE range. However, if the configuration shows that BPF support is disabled because CONFIG_BPF is set to N, all associated source files, including kernel/bpf/verifier.c, are excluded from the compilation. Thus, our proposed attribution method does not witness the affected file presence during the

---

1https://gsa.debian.org/kernel-team/linux/~blob/master/debian/config/arm64/config, Accessed: 2022-09-05.
2https://www.gnu.org/licenses/gpl-faq.html, Accessed: 2022-09-05.
3https://nvd.nist.gov/vuln/detail/CVE-2017-17863, Accessed: 2022-09-05.
We perform a case study to evaluate the reliability of our enriched version-based Linux kernel CVE attribution in large-scale static analyses. For this purpose, we let our pipeline analyze the Home Router Security Report 2020 [7] corpus, which vendors reported to yield high false-positive rates using version-based CVE matching. We raise two research questions:

R1 Our methodology requires access to specific information in firmware samples and CVE repositories. How many samples and CVEs fulfill these modalities? How applicable is our approach in a real-world scenario?

R2 With version-based CVE matching as baseline, what impact has the methodology on result reliability?

In the following subsections, we first provide detailed information on our experiment and used dataset (IV-A). Then, we present the results and analyze them within the context of both stated research questions (IV-B and IV-C, respectively).

A. Experiment & Firmware Corpus

Experiment Execution. We deploy our static analysis CVE attribution pipeline on a system with AMD Ryzen 7 2700x processor and 32 GiB DDR4 RAM, running Ubuntu 20.04.4 LTS. FACT v4.0 (commit 38df4883) is used in the first pipeline stage. We extract each firmware of the Home Router Security Report 2020 [7] corpus and apply the required analysis plugins CPU Architecture, Software Components, and Kernel Configuration (cf., Section III-A). The second pipeline stage executes on the same machine based on a snapshot of the NVD [23] – taken on 2022-08-30. The snapshot has records for 2,910 Linux kernel CVEs attributable through CPE. For each component in our system, we collect details on ingress and egress data, including plugin results, version-based CVE matches, and filtering decisions.

Firmware Corpus. The analyzed Home Router Security Report [7] corpus is publicly documented\(^3\), reconstructable, and consists of firmware from 127 home routers available in the European market. Devices of seven well-known vendors are included: ASUS, AVM, D-Link, Linksys, Netgear, TP-Link, and Zyxel. Samples were scrapped on 2020-03-27.

Figure 3 shows the distribution of Linux kernel versions detected by FACT across all firmware images. Numbers in parentheses and on top of bars count sample sizes per vendor and kernel. Patch levels are clustered by major and minor release for illustrative purposes, but are considered during CVE attribution. Across all 127 samples, 121 binary distributed Linux kernels from v2.4.20 to v4.4.60 are included. 11 firmware images are not analyzable due to failed operating system analysis or unpacking errors. Note that firmware can contain multiple kernels, e.g., embedded devices may consist of subcomponents running their own systems.

\(^3\)https://github.com/fkie-cad/embedded-evaluation-corpora/blob/master/2020/ FKIE-HRS-2020.md, Accessed: 2022-09-05.
rows designate effective requirement fulfillment rates over all analyzed firmware images and Linux kernel CVEs.

For requirement S1, FACT successfully extracts 116 out of 127 firmware images. The analyses detect at least one kernel version in all extractable firmware, and ISAs in 103 of them. However, our Kernel Configuration plugin finds build information in only 44. As this plugin depends on results from previous analyses (cf., Section III), the matches are a subset of information in only 44. As this plugin depends on results from

Table I distributes all 2,910 Linux kernel CVEs across these classes, showing that the proposed approach is applicable to 1,872 (64.33%) kernel CVEs. For CVEs with no included file reference, the approach falls back to version-based CVE matching and, thus, can not add value to result reliability.

C. R2 Analysis – Impact on CVE Attribution Result Reliability

With version-based Linux kernel CVE matching as baseline, what impact has our attribution pipeline on result reliability? We approach research question R2 by analyzing the attribution results of all 44 firmware images our methodology is applicable to (cf., Section IV-B). Subject samples include kernels ranging from v3.4.0 to v4.4.60. Out of these, only one still receives mainline updates at the time of this evaluation (4.4.x).

The baseline method attributes a median of 1,196 CVEs per firmware image, which is roughly 40% of all Linux kernel CVEs present in the NVD. A possible explanation lies within unsound and/or unmaintained CVE records in the NVD [14], [15]. Yet, such imprecise data would also imply the existence of false-negatives that should have been attributed to the kernel version, but were not due to incorrect CPE. An argument in favor of these results is the amount of end of life kernels in the dataset. However, based on the results we present in the following paragraphs, there is reason to assume that the baseline yields exceedingly high false-positive rates.

Version-based CVE attribution is an intermediate result of our methodology (cf., Section III). To estimate the impact our pipeline has on result reliability, we consolidate all decisions of the build-log assisted filtering to classify them into four categories of verdict confidence:

- **Applicable (High)** – CVE references affected files and full file path is witnessed in build log.
- **Not Applicable (High)** – CVE references affected files but none of them is present in the build log.
- **Applicable (No File Match, Low Confidence)**
- **Applicable (Full Path Match, High Confidence)**
- **Applicable (File Only Match, Medium Confidence)**
- **Not Applicable (Low)**
- **Not Applicable (High)**

Fig. 5: Filter verdict distribution of our pipeline relative to the baseline CVE attribution results for each of the 44 analyzed kernels. Each entry on the horizontal axis represents a unique firmware. We classify them into four different verdict confidence categories. With high confidence, our methodology marks around 68.37% of all baseline matches as false-positive and 12.04% as true-positive candidates (medians). Relative path matches with medium confidence match verdict are negligible with 0.19%.

| Requirement (FACT Analysis Success) | FW Matches | Fulfilled |
|------------------------------------|------------|-----------|
| Extraction                         | 116        | 0.9133    |
| Kernel Version                     | 116        | 0.9133    |
| Architecture Detection             | 103        | 0.8110    |
| Kernel Configuration               | 44         | 0.3464    |

Table I: Method Applicability Analysis for the Firmware Corpus

| Requirement (File Reference in Linux Kernel CVE) | CVE Matches | Fulfilled |
|-------------------------------------------------|-------------|-----------|
| Full Path Reference                             | 1743        | 0.5990    |
| File Only Reference                             | 129         | 0.0443    |
| No Reference                                    | 1098        | 0.3567    |
• **Applicable (Medium)** – CVE references affected files, but does not state full file paths. A file was matched and seen in the build log, but ambiguity exists due to duplicate names in the source tree.

• **Applicable (Low)** – No file references, we can not decide on applicability and fall back to version-based matching.

The idea is to map persuasiveness of additional evidence the pipeline gathers within a trial: File matches are witnesses for CVE applicability, but not every match is equally credible.

Figure 5 shows the filter verdict distribution of our pipeline relative to the baseline CVE attribution results for each analyzed kernel. Versions are ordered from oldest (left) to newest (right). Note that a single kernel was found in each one of the 44 analyzed samples. Thus, each entry on the horizontal axis represents a unique firmware. In the following, all discussed distribution values are medians across all samples.

The proposed Linux kernel CVE attribution methodology is able to make a medium to high confidence decision for 80.6\% of all version-based matches. The portion of high confidence applicable CVE matches is 12.04\%. Relative path matches yielding medium confidence applicability are negligible with 0.19\%. As indicated by the bottom bars belonging to the class of Not Applicable (High), our pipeline attributes 68.37\% of all version-based CVE matches as *false-positives* and filters them out of the result set. In numbers - out of the median 1,196 matches per firmware, we reduce the set of potentially applicable CVEs to roughly 378. Thus, we significantly reduce the result set of potentially applicable CVEs requiring manual verification by analysts and vendors. The portion of low confidence applicability due to missing file references is 19.4\%. Unfortunately, for this class of matches our methodology does not generate added value.

**V. LIMITATIONS**

We identify methodological shortcomings in three dimensions: applicability, sound ground truth, and functionality.

In terms of applicability, our Linux kernel CVE attribution pipeline is bound to FACT’s static analysis success. If the kernel version, ISA, and build configuration remain unknown, our method can not identify possibly included components for reliable CVE filtering. Then, the pipeline becomes inapplicable. Yet, the case study in Section IV shows that (in the used firmware corpus) there is still a considerable amount of firmware fulfilling all requirements.

As for sound ground truth, reliable and true-positive CVE attribution is limited by the quality of its underlying dataset. If Linux kernel CVE records do not reference truly affected versions and source files, the proposed mechanisms introduce false-positive, but also false-negative matches. In this case, result reliability is negatively affected. Our assumption of vendors using mainline kernels is another limiting factor that affects reliability, but a methodical necessity due to missing insider information. Vendors may cherry-pick patches or introduce custom fixes, which are not detectable by our approach. While some of the modifications might be obtainable through GPL portals, we identify the issue of scalable accessibility.

Regarding functional limits, we stress the inherited limitations of static analyses. They may use heuristics to find indicators of possible bug presence, but can hardly serve definitive proof – which requires triggering the bug.

Finally, the conducted case study is limited in its validity, as the used corpus is missing in device class heterogeneity.

**VI. CONCLUSION**

In this paper, we focused on improving result reliability of version-based CVE matching for the special case of binary Linux kernels in large-scale static firmware analyses. Heterogeneous hardware properties, modularity, numerous development streams, and vendor-specific builds cause high false-positive rates. This is because the attribution method does not check for vulnerable component presence in binary images when filtering CVEs.

Despite general automation issues due to unsound or incomplete data in CVE repositories and common challenges in binary firmware analyses, we found supplementary filter data in Linux issue descriptions and firmware samples to reduce the set of false-positive matches in scale. We enriched naive version-based CVE matching with a static attribution pipeline that detects kernel configurations and ISAs in firmware images to reconstruct the kernel build process and guess included source files. This data then serves as filter using kernel CVEs where affected files are explicitly stated.

The case study shows that, with the limitations discussed in Section V in mind, our approach is scalable and moderately applicable: For 34.64\% of all 127 considered home router firmware images, the technical requirements are fulfilled and about 65\% of all Linux kernel CVEs reference affected files in their description.

With naive version-based matching as baseline, the introduced approach generates a high confidence filter verdict for 80.6\% of all considered CVEs and reduces the result set by 68.37\%: CVEs affecting components probably absent from binary kernel samples are successfully eliminated. While a non-negligible amount of CVEs that our method can not reliably filter remains, we conclude that the proposed attribution pipeline is a promising step towards more reliable and scalable static CVE attribution. Security analysts are still required to verify the true applicability of a bug, but our systematic and automated filtering may at least reduce their manual efforts.

Stage one of our pipeline is part of the publicly available FACT [16], stage two is a set of standalone scripts available at https://github.com/fkie-cad/cve-attribution-s2, and our case study corpus is documented for reconstruction at https://github.com/fkie-cad/embedded-evaluation-corpus.

**VII. FUTURE WORK**

In future work, we want to address missing device class heterogeneity present in our case study corpus. Aside of identifying and implementing additional filter criteria, we evaluate options to combine the proposed methodology with *linuxkernelscves.org* [25]. The CPE data used for version matching is of varying quality [15] and may introduce false-positives.
and -negatives not caught by our methodology. A more fine-granular commit-based version tracking as offered by [25] is a promising addition to our pipeline. However, a thorough review of the automatically applied method is required before adapting this data source over the de-facto standard of the NVD.

REFERENCES

[1] A. Giri et al., “Internet of Things (IoT): A Survey on Architecture, Enabling Technologies, Applications and Challenges,” in Proc. of the 1st International Conference on Internet of Things and Machine Learning (IML ‘17). Liverpool, United Kingdom: Association for Computing Machinery, 2017, pp. 1–12. [Online] https://doi.org/10.1145/3109761.3109768

[2] H. Xu et al., “A Survey on Industrial Internet of Things: A Cyber-Physical Systems Perspective,” IEEE Access, vol. 6, pp. 78,238–78,259, 2018. [Online] https://doi.org/10.1109/ACCESS.2018.2884006

[3] S. M. R. Islam et al., “The Internet of Things for Health Care: A Comprehensive Survey,” IEEE Access, vol. 3, pp. 678–708, 2015. [Online] https://doi.org/10.1109/ACCESS.2015.2437951

[4] N. Neshenko et al., “Demonstifying IoT Security: An Exhaustive Survey on IoT Vulnerabilities and a First Empirical Look on Internet-Scale IoT Exploitations,” IEEE Communications Surveys & Tutorials, vol. 21, no. 3, pp. 2702–2733, 2019. [Online] https://doi.org/10.1109/COMST.2019.2910750

[5] Y. David, N. Partush, and E. Yahav, “FirmUp: Precise Static Detection of Common Vulnerabilities in Firmware,” in Proc. of the 23rd International Conference on Architectural Support for Programming Languages and Operating Systems (ASPLOS ‘18). Williamsburg, USA: Association for Computing Machinery, 2018, pp. 392–404. [Online] https://doi.org/10.1145/3173162.3171757

[6] A. Costin et al., “A Large-Scale Analysis of the Security of Embedded Firmwares,” in Proc. of the 23rd USENIX Conference on Security Symposium (SEC ’14). San Diego, USA: USENIX Association, 2014, p. 95–110. [Online] https://dl.acm.org/doi/10.5555/2671225.2671232

[7] P. Weidenbach and J. vom Dorr, Home Router Security Report 2020. Fraunhofer Institute for Communication, Information Processing and Ergonomics (FKIE), Technical Report, 2020. [Online] https://www.fkie.fraunhofer.de/en/press-releases/Home-Router.html

[8] The MITRE Corporation, “Official CVE Program Database,” Accessed: 2022-09-05. [Online] https://www.cve.org/

[9] C. Wright et al., “Challenges in Firmware Re-Hosting, Emulation, and Analysis,” ACM Computing Surveys, vol. 54, no. 1, pp. 1–36, 2021. [Online] https://doi.org/10.1145/3423167

[10] A. Qasem et al., “Automatic Vulnerability Detection in Embedded Devices and Firmware: Survey and Layered Taxonomies,” ACM Computing Surveys, vol. 54, no. 2, pp. 1–42, 2021. [Online] https://doi.org/10.1145/3432893

[11] D. Chen et al., “Towards Automated Dynamic Analysis for Linux-based Embedded Firmware,” in Proc. of the 2016 Symposium on Network and Distributed System Security (NDSS ‘16). San Diego, USA: Internet Society, 2016, pp. 1–16. [Online] https://doi.org/10.14722/nds.2016.23415

[12] M. Kim et al., “FirmAE: Towards Large-Scale Emulation of IoT Firmware for Dynamic Analysis,” in Proc. of the 2020 Annual Computer Security Applications Conference (ACSAC ‘20). Austin, USA: Association for Computing Machinery, 2020, pp. 733–745. [Online] https://doi.org/10.1145/3427228.3427294

[13] S. Lipp, S. Banescu, and A. Pretschner, “An Empirical Study on the Effectiveness of Static C Code Analyzers for Vulnerability Detection,” in Proc. of the 31st ACM SIGSOFT International Symposium on Software Testing and Analysis (ISSTA ’22). Virtual, Republic of Korea: Association for Computing Machinery, 2022, p. 1–12. [Online] https://doi.org/10.1145/3533767.353438

[14] X. Tan et al., “Locating the Security Patches for Disclosed OSS Vulnerabilities with Vulnerability-Commit Correlation Ranking,” in Proc. of the 2021 ACM SIGSAC Conference on Computer and Communications Security (CCS ‘21). Virtual, Republic of Korea: Association for Computing Machinery, 2021, p. 3262–3299. [Online] https://doi.org/10.1145/3460120.3484593

[15] L. A. Benthin Sanguino and R. Uetz, “Software Vulnerability Analysis Using CPE and CVE,” ArXiv, 2017. [Online] https://doi.org/10.48550/arXiv.1705.05347

[16] Fraunhofer FKIE, “FACT - Firmware Analysis and Comparison Tool,” Accessed: 2022-09-05. [Online] https://github.com/fkie-cad/FACT_core

[17] ONEKEY GmbH, “ONEKEY Automated Firmware Analysis Platform,” Accessed: 2022-09-05. [Online] https://onekey.com/

[18] NetRise Inc., “NetRise Platform - Next-Generation Firmware & IoT Security Platform,” Accessed: 2022-09-05. [Online] https://www.netrise.com

[19] B. Zhao et al., “A Large-Scale Empirical Analysis of the Vulnerabilities Introduced by Third-Party Components in IoT Firmware,” in Proc. of the 31st ACM SIGSOFT International Symposium on Software Testing and Analysis (ISSTA ’22). Virtual, South Korea: Association for Computing Machinery, 2022, p. 442–454. [Online] https://doi.org/10.1145/3533767.3534366

[20] I. U. Haq and J. Caballero, “A Survey of Binary Code Similarity,” ACM Computing Surveys, vol. 54, no. 3, pp. 1–38, 2021. [Online] https://doi.org/10.1145/3446371

[21] R. Baldoni et al., “A Survey of Symbolic Execution Techniques,” ACM Computing Surveys, vol. 51, no. 3, pp. 1–39, 2018. [Online] https://doi.org/10.1145/3182657

[22] V. J. Manès et al., “The Art, Science, and Engineering of Fuzzing: A Survey,” IEEE Transactions on Software Engineering, vol. 47, no. 11, pp. 2312–2331, 2021. [Online] https://doi.org/10.1109/TSE.2019.2946563

[23] National Institute of Standards and Technology, “National Vulnerability Database,” Accessed: 2022-09-05. [Online] https://nvd.nist.gov/

[24] R. Habalov and T. Schmid, “Vulcode-DB,” Accessed: 2022-09-05. [Online] https://www.vulcode-db.com/

[25] N. Luedtke and Contributors, “Linux Kernel CVEs,” Accessed: 2022-09-05. [Online] https://www.linuxkernelcves.com/

[26] Microsoft, “Binwalk,” Accessed: 2022-09-05. [Online] https://github.com/com/ReFirmLabs/binwalk

[27] Google, “YARA - The pattern matching swiss knife for malware researchers (and everyone else),” Accessed: 2022-09-05. [Online] https://virustotal.github.io/yara/

[28] T. Klein and B. Davis. checksec.sh. [Online] https://github.com/tfeld/checksec.sh

[29] Linaro Ltd., “DeviceTree Specification,” Release v0.4-rc1, 2021. [Online] https://devicetree.org/devicetree-specification/releases/download/v0.4-rc1/devicetree-specification-v0.4-rc1.pdf