Build It Clean: Large-Scale Detection of Code Smells in Build Scripts

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Abstract—Build scripts are files that automate the process of compiling source code, managing dependencies, running tests, and packaging software into deployable artifacts. These scripts are ubiquitous in modern software development pipelines for streamlining testing and delivery. While developing build scripts, practitioners may inadvertently introduce code smells. Code smells are recurring patterns of poor coding practices that may lead to build failures or increase risk and technical debt. The goal of this study is to aid practitioners in avoiding code smells in build scripts through an empirical study of build scripts and issues on GitHub. We employed a mixed-methods approach, combining qualitative and quantitative analysis. We conducted a qualitative analysis of 2000 build-script-related GitHub issues. Next, we developed a static analysis tool, Sniffer, to identify code smells in 5882 build scripts of Maven, Gradle, Cmake, and Make files, collected from 4877 open-source GitHub repositories. We identified 13 code smell categories, with a total of 10,895 smell occurrences, where 3184 were in Maven, 1214 in Gradle, 337 in CMake, and 6160 in Makefiles.

Our analysis revealed that Insecure URLs were the most prevalent code smell in Maven build scripts, while Hardcoded Paths/URLs were commonly observed in both Gradle and CMake scripts. Wildcard Usage emerged as the most frequent smell in Makefiles. The co-occurrence analysis revealed strong associations between specific smell pairs of Hardcoded Paths/URLs with Duplicates, and Inconsistent Dependency Management with Empty or Incomplete Tags, indicating potential underlying issues in the build script structure and maintenance practices. Based on our findings, we recommend strategies to mitigate the existence of code smells in build scripts to improve the efficiency, reliability, and maintainability of software projects.

I. INTRODUCTION

Build scripts are ubiquitous in modern software development, facilitating the automation of complex software application compilation, testing, and deployment processes. Build scripts are used to transform source code into deliverable artifacts. Developers use build tools such as Maven and Gradle to define their respective build systems [1] and maintain consistency and reproducibility across diverse environments. To automate the software development and testing process, the majority of well-maintained software projects make use of build tools like Maven and Gradle [2]. According to

JetBrains [3], Maven and Gradle are popular build tools with 71% and 48% usage in the industry, respectively.

As software systems grow in scale and functionality, build scripts become increasingly complex [4] and might require frequent maintenance [5], which can negatively impact overall project quality and developer productivity [6]. Consequently, these scripts become susceptible to various code smells [7].

Code smells are indicators of potential underlying issues in the design and implementation of software, which increases the fault-proneness [8] and makes the system more difficult to maintain [9] and understand [10]. Code smells are the symptoms of poor design and implementation [11], which leads to technical debt [12]. Code smell introduces bugs, affects software maintainability [13], and causes developers' burden [14]. Early detection and remediation of these smells could aid in reducing higher maintenance costs, improve software reliability, and mitigate security risks throughout the automated software development life cycle [15].

Prior studies showed that files without code smells exhibit approximately 33%-65% lower risk of fault compared to those containing code smells [16], [17]. Code smells are important predictors of build failures, indicating a link between code quality in build scripts and build reliability [18]. Moreover, broken builds could disrupt team productivity and negatively impact overall project performance [19]. Previous studies have explored the adverse effects of code smells in platforms such as Travis CI [20], Infrastructure as Code (IaC) [21], and source code [22]. However, despite the widespread use of build scripts in modern software development, particularly within Continuous Integration and Continuous Deployment (CI/CD) pipelines, to our knowledge, a systematic analysis of the presence of code smells in the context of build scripts has not been performed yet. Overlooked code smells in build scripts could inadvertently facilitate the spread of bad coding practices, thereby impeding the adaptability and maintainability of software systems [23], [24]. In this paper, we aim to systematically investigate, identify, and quantify code smells in the context of build scripts, employing both static analysis techniques and qualitative assessments.

The goal of this paper is to aid practitioners in avoiding code smells in build scripts through an empirical study of build scripts and issues on GitHub.

For this, we aim to address the following research questions:

- **RQ1:** What code smells occur in build scripts?
- RQ2 How frequently do code smells occur in build scripts?

We address our research questions by examining four types of build scripts: Maven [25], Gradle [26], CMake [27], and Make [28], as well as build script-related GitHub issues collected from open-source GitHub repositories. We conducted a qualitative analysis of 2,000 GitHub issues to identify prevalent code smells, following established guidelines for qualitative research [29]. Next, we collected build scripts from GitHub and leveraged Large Language Models (LLMs) to identify potential code smells in build scripts. We used six general and code-oriented LLMs i.e., ChatGPT4, ChatGPT4o, Codellama, Llama 8B, Llama 13B, and Mistral, to detect potential code smells in the build script. Furthermore, we mapped each code to its corresponding Common Weakness Enumeration (CWE) to establish standardized categorizations of the underlying weaknesses. Based on our qualitative study and findings from the language models, we developed a static analysis tool, "Sniffer", to automatically detect the presence of code smells. Further, we developed an Oracle through a user study to compare our tool's performance against human evaluation. For our empirical analysis, we gathered 5882 build scripts from 4877 open-source repositories. We measured the occurrence, frequency, and co-occurrence of the code smells in the four types of build scripts. The contributions of our study are outlined below:

- Identification and detailed classification of code smells specifically prevalent in build scripts for Maven, Gradle, CMake, and Make.
- Development and evaluation of "Sniffer," a novel static analysis tool to automatically detect code smells in build scripts.
- 3) Developed an Oracle to compare our linter performance against the human evaluation of code smells.
- 4) Analysis of the occurrence and frequency of build scriptspecific code smells.

We organized this paper as follows: background information, with related work in Section II, the methodologies and results of identifying code smells in Section III. Development methodology and evaluation of Sniffer in Section IV. Empirical Analysis of Build Scripts in Section V. Detailed discussion and recommendation in Section VI. Sections VII and VIII cover threats to validity. Section IX provides conclusions.

II. BACKGROUND AND LITERATURE REVIEW

The concept of code smells was popularized by Kent Beck on WardsWiki in the late 1990s, and later usage of the term increased by Fowler [11], which was initially focused on identifying patterns in source code that may indicate deeper design or maintenance problems. Later, multiple works focused on detecting code smells in several code base including source code [30] [31], [32], configuration code [33], and Infrastructure as Code (IAC) [34]. Barrak et al. [18] demonstrate that code and test smells are strong predictors of build failures. According to Adams et al. [35], there is a strong co-evolutionary relationship between source code and build scripts. Build scripts have prevalent use in automating the compilation, testing, packaging, and deployment of software and are also susceptible to similar code smells. By encapsulating a sequence of commands and configurations, build scripts eliminate the need for manual intervention, reducing the risk of human error and accelerating the software delivery pipeline [7]. Since build scripts need to be synchronized with the source code and the entire build environment, neglecting code smells in build scripts often leads to build failures [36]. Saidani and Ouni [20] showed that integrating bad smell detection raises build failure prediction accuracy by 4%. Addressing performance-related smells can also yield greater benefits: Zhang et al. [36] recorded a 12.4% average improvement in build performance once performance-related smells are addressed.

Further, the effort of maintaining build systems is nontrivial. Research by McIntosh et al. [4] showed that build maintenance tasks account for up to 27% of the overhead in source code development and 44% in test development. Moreover, 22% of commits and 27% of development tasks directly involve build scripts, highlighting the substantial developer effort spent on managing build infrastructure. Vassallo et al. [37] observe that smells can lead to broken builds and integration delays, disrupting team productivity and software delivery timelines.

Despite the importance of build scripts in modern software development workflows, build scripts remain understudied. While source code smells have been extensively studied and cataloged in other codebases [30], [38]–[41], there is no comprehensive or standardized taxonomy of smells for build scripts. Moreover, security incidents such as the XZ Utils backdoor [42] have underscored how malicious or negligent configurations in build processes can act as vectors for supply chain attacks. These highlight the gap and need for a systematic analysis of build script quality to identify both maintenance and security-related smells. Given these gaps, this study aims to systematically identify and categorize code smells specific to build scripts across multiple build systems and to suggest their potential mitigation to enhance the maintainability and security of build automation processes.

III. INVESTIGATING CODE SMELLS IN BUILD SCRIPTS

We conducted a mixed-method study with qualitative and quantitative parts to answer our research questions. Below we discussed the methods for RQ1 in Section III-A and the findings of RQ1 in Section III-B.

In steps of methodology: i) Qualitative analysis of GitHub issues. ii) Qualitative Analysis of build scripts LLMs. iii) Code smells to CWE mapping.

1) Qualitative Analysis on GitHub Issues: Our qualitative analysis consists of three phases: platform selection, data collection, and qualitative coding.

Platform Selection: For this study, we selected GitHub as it is a widely used platform for open source software development [43] and scientific research [44]. According to the StackOverflow 2024 survey [45], Maven, Gradle, Cmake, and Make are the most popular and widely used build system tools; as such, we selected these build tools for our study.

Data Collection: We performed a keyword-based search within the GitHub repositories using the Rest API and GraphQL. We specifically searched for build scripts and code smell-related keywords in the GitHub repositories and issues' metadata, including titles, descriptions, and labels for the selected build type. Two authors collaboratively reviewed and iteratively refined the search queries for their relevance and accuracy based on prior studies on code smells and practitioner blog posts [33], [46]–[49]. The search strings included:

"codesmell", "code smell", "bad practice", "bad smell", "HTTP external download", "empty password", "long parameter", "long method", "inconsistent version", "abandoned dependencies", "unused dependency", "duplicate code", "long method", "admin by default", "anti-pattern", "hardcoded paths", "duplicated configuration", "duplicate code", "conditional complexity", "Dead code", "inconsistent name", "complex build logic", "inconsistent dependency versions", "unused dependencies", "excessive build times", "lack of modularity", "excessive task dependencies", "Path-misconfiguration".

Following the process, we collected 7533 GitHub issues. Further removing the duplicates, 7104 unique issues remain.

Qualitative Coding: We conducted a qualitative analysis to obtain a summarized overview of recurring bad coding practices in build scripts and to gain insight into potential code smells. For this process, we randomly selected 200 issues of each type of build script (Maven, Gradle, CMake, and Make), totaling 800 GitHub issues out of 7104 issues. Two authors independently conducted a descriptive qualitative analysis [50] on these sampled issues. To our knowledge, at the time of this study, no prior research or predefined list of code smells specific to build scripts was available. To enhance the completeness of our qualitative findings, we compared the 800 issues analyzed with the remaining dataset using the Jaccard similarity index [51]. We employed the Jaccard score to identify and prioritize dissimilar issues for further analysis based on the assumption that similar issues are likely to yield similar code smell detections as in the first 800 issues. Consequently, issues with the lowest Jaccard scores were selected as starting points for further investigation. We continued iterative analysis of GitHub issues until no new code smells emerged. Following the process, we analyzed an additional 1200 issues, 300 issues from each building

type, ultimately reaching a saturation point [52], where no new code smells were identified. Following the process, we qualitatively coded 2000 GitHub issues. After conducting descriptive coding, the authors collaboratively finalized the code smells list and addressed any conflicts through a negotiated agreement approach [53]. Disagreements were resolved either by eliminating inappropriate categories for code smells or by merging closely related categories to form a unified and coherent categorization. Following the processes, we make an initial list of code smells based on GitHub issue analysis.

2) Qualitative Analysis of build scripts leveraging LLM: In this phase, we leveraged Large Language Models (LLMs) to analyze and detect code smells within build scripts. The primary objective of employing LLMs was to explore their potential for automating the identification of code smells, given their advanced capabilities in understanding both natural language and programming code semantics. Recent studies have demonstrated that LLMs exhibit strong performance in a range of software engineering and security tasks [54]–[56]. Details are given below.

Data Collection: For our build script analysis, we applied a multi-faceted approach to construct a comprehensive dataset of build scripts from open-source projects. We developed an automated Python script that utilizes the GitHub API to identify and retrieve build files specifically associated with four selected build systems: Maven, Gradle, CMake, and Make. The script was configured to search for build script filenames corresponding to these systems, such as:

• Maven: pom.xml

• Gradle: build.gradle and build.gradle.kts

• CMake: CMakeLists.txt

• Make: Makefile (and files with the .mk extension)

For each build system, we employed a system-specific search query (e.g., filename:pom.xml) and iteratively retrieved the search results from GitHub. To maximize coverage, multiple pages of results were fetched. For search results, we collected relevant metadata, including the repository name, repository URL, and the raw URL of the build script. Next, we collected the exact build script using the corresponding URL. The data collection steps utilized broad GitHub queries and retrieved results from multiple pages, without restrictions on project domain, size, or popularity. This approach allowed us to collect a diverse set of build scripts from projects of varying maturity levels and development practices. Following the data collection step and removing duplicate entries, our final dataset comprised 2,134 distinct build scripts.

Selection of LLM: We leveraged LLMs to detect code smells in build scripts. We selected six LLM models with a mix of general code-based, paid, and open-source models, namely ChatGPT 4, ChatGPT 4o, LLaMA 8B, LLaMA 13B, CodeLLaMA, and Mistral. First, we selected 100 scripts from the collected build scripts. Next, we applied zero-shot prompting across six LLMs, instructing them to analyze the build scripts and identify instances of code smells. We provided an initial list of potential code smells identified in our qualitative analysis of GitHub issues. The models were tasked with

detecting both the predefined code smells and any additional, previously unrecognized code smells they could infer from the scripts.

Validation of LLM: To evaluate the models' performance, three authors manually analyzed the same 100 scripts individually. The results from this manual analysis were then compared against the results provided by the six LLMs' outputs. To avoid potential bias, the first author was responsible for executing the LLMs and comparing their output with the manual analysis, while the second, third, and fourth authors conducted the manual evaluations and resolved any conflict through iterative discussion and following negotiation agreement [53]. Among the analyzed LLMs, ChatGPT-40 showed the highest recall, accurately identifying the majority of true positive code smells, presented in Table I. As a result, ChatGPT-40 was selected for further analysis.

Analysis with LLM: We analyzed 2,134 collected build scripts using ChatGPT-40, following a consistent prompt and procedure. This process provided an extensive list of code smells. To facilitate structured analysis, we grouped similar code smells into broader smell categories. For instance, LLM-generated responses such as "HTTP URL for Maven Central," "Insecure Repository URL," and "HTTP Repository URL" were grouped under the category "Insecure URLs," as they reflect a common pattern of using unsecured links within build scripts. Through this categorization process, 13 distinct code smell categories were identified, provided in Table II.

TABLE I
LLMs Comparison Based on Recall

	Maven	Gradle	Cmake	Make
Llama 8B	41%	36%	27%	13%
Llama 13B	32%	38%	20%	13%
Codellama	29%	34%	14%	16%
Mistral	41%	43%	31%	13%
ChatGPT 4	59%	52%	36%	33%
ChatGPT 4o	78%	75%	52%	42%

3) Code Smells to CWE Mapping: To assess the security relevance of the identified code smells in build scripts, we mapped each instance to corresponding entries in the Common Weakness Enumeration (CWE) database. We selected CWE as the reference framework due to its standardized taxonomy of software security weaknesses and proper maintenance by the cybersecurity community [57]. For example, the smell "Hardcoded credential" was mapped to both CWE-798: Use of Hard-coded Credentials and CWE-259: Use of Hardcoded Password [57]. To be consistent with the objectivity in the mapping process, two authors independently performed mapping between code smells and CWEs. Further, we resolved our conflicts through discussion with another author. Our evaluations demonstrate perfect consistency, resulting in a Cohen's Kappa score of 1.0, which indicates perfect inter-rater reliability. A list of the identified code smells across different types of build scripts with the associated CWE is in Table II. B. Answer to RQ1: What code smells occur in build scripts?

In this section, we provided an answer to RQ1. Following our methodology for RQ1, we identified thirteen code smell categories. Each of the identified code smells is described below. An annotated example Maven script with all the identified code smells is presented in Figure 1.

- Hardcoded Credentials: Hardcoded credentials refer to the recurring pattern of embedding authentication or sensitive information such as usernames, passwords, API tokens, or private keys directly within build scripts. This approach poses a major security risk as sensitive information may be inadvertently exposed through version control. As a result, secrets can be exposed to public repositories and cause unauthorized access to the system [21]. This smell aligns with CWE-798: Use of Hardcoded Credentials and CWE-259: Use of Hardcoded Password, which highlights the vulnerability of storing sensitive data in an unprotected and immutable manner.
- Hardcoded Paths / URLs: This smell refers to the recurring pattern of the direct inclusion of absolute paths or fixed URLs in build scripts. Embedding absolute paths or fixed URLs directly into scripts can lead to failures when the code is executed in different environments, as these paths may not exist or may differ across systems. This could reduce the portability and adaptability of the build process [58], [59]. Furthermore, hardcoded network paths can expose the system to untrusted locations. This smell aligns with CWE-427: Uncontrolled Search Path Element and CWE-706: Use of Incorrectly-Resolved Name or Reference.
- Deprecated Dependencies: This smell refers to the recurring pattern of using abandoned or not-maintained dependencies. Using deprecated libraries or APIs in build configurations is indicative of poor dependency management [60]. Deprecated components are typically no longer maintained or updated and may harbor known vulnerabilities. This smell is closely associated with CWE-1104: Use of Unmaintained Third-Party Components, which refers to the risks of depending on obsolete software packages.
- Outdated Dependencies: This smell refers to a practice
 when build scripts reference older versions of dependencies for which more secure or stable releases exist.
 Persisting with outdated libraries increases the likelihood
 of exposure to known vulnerabilities and creates an attack
 vector [61]. As with deprecated components, this issue is
 categorized under CWE-1104, emphasizing the need for
 timely dependency upgrades.
- **Duplicates:** Duplicate code declarations occur when the same dependency, code, or configuration is redundantly included in the build script [62], [63]. This practice leads to bloated scripts, increases maintenance overhead, and may cause unexpected behaviors due to overriding rules. Although there is no exact CWE that captures this issue, it falls under the CWE-710: Improper Adherence to Code Standards, which represents poor coding practices.

TABLE II LIST OF IDENTIFIED CODE SMELL

Code Smell Category	Maven	Gradle	Cmake	Make	Common Weakness Enumeration (CWE)				
Hardcoded Credentials	*	*	*	*	CWE-798: Use of Hard-coded Credentials				
Hardcoded Credentials				· .	CWE-259: Use of Hard-coded Password				
Hardcoded Paths/ URLs	*	*	* * (CWE-427: Uncontrolled Search Path Element				
Hardcoded Faths/ UKLs					CWE-706: Use of Incorrectly-Resolved Name or Reference				
Deprecated Dependencies	*	*	*	*	CWE-1104: Use of Unmaintained Third-Party Components				
Outdated Dependencies	*	*	*	*	CWE-1104: Use of Unmaintained Third-Party Components				
Duplicate	*	*	*	*	CWE-710: Improper Adherence to Coding Standards				
Suspicious Comments	*	*	*	*	CWE-546: Suspicious Comment				
Insecure URLs	*	*	*	*	CWE-319: Cleartext Transmission of Sensitive Information				
Empty/Incomplete Tags	*	*			CWE-611: Improper Restriction of XML External Entity Reference (XXE)				
Complexity			*	*	CWE-710: Improper Adherence to Coding Standards				
Lack Error Handling	*	*	*	*	CWE-391: Unchecked Error Condition				
Wildcard Usage	*	*	*	*	CWE-829: Inclusion of Functionality from Untrusted Control Sphere				
Missing Dependency Version	*	*	*	*	CWE-440: Expected Behavior Violation				
Inconsistent Dependency Management	*	*			CWE-439: Behavioral Change in New Version or Environment				
inconsistent Dependency Management					CWE-710: Improper Adherence to Coding Standards				

- Suspicious Comments: This smell is the recurring pattern of placing information in comments that points to unresolved defects, missing functionality, or system weaknesses. The smell is related to CWE-546: Suspicious Comment. Examples include comments containing "TODO," or "FIXME," which often indicate latent issues that have not been addressed [64].
- Insecure URLs: Using non-secure URLs (i.e., HTTP instead of HTTPS) for fetching dependencies or uploading artifacts is considered a code smell. This practice exposes communication channels to man-in-the-middle (MITM) attacks and tampering [65]; which corresponds to CWE-319: Cleartext Transmission of Sensitive Information.
- Empty/Incomplete Tags: This smell refers to the use of XML elements without content (e.g., < modelVersion >< /modelVersion >), which can lead to undefined behavior or misinterpretation by tools. This smell is linked to CWE-611: Improper Restriction of XML External Entity Reference (XXE), indicating a lack of standardization. As this is an XML-based code smell, in our analysis, we found that this type of code smell exists only in Maven and Gradle.
- Complexity: This code smells refers to overly complex logic in build scripts such as nested conditionals, inline shell commands, or convoluted plugin chains. This smell is also known as conditional complexity, using lengthy, cascading if statements or switch/case [66]. The existence of such smells reduces maintainability and increases the likelihood of misconfiguration. This smell is linked to CWE-710: Improper Adherence to Coding Standards.
- Lack of Error Handling: For build scripts, this smell refers to a lack of error checking or passing the code with the error. For example, if the maven script "sql-maven-plugin" is configured with <onError>continue</onError>, which means that the build will continue even if errors occur during SQL execution. This can mask issues that should be addressed before deployment. It is a code smell because it can lead to overlooking major errors, resulting in unstable

- or incorrect build artifacts. This smell falls under CWE-391: Unchecked Error Condition.
- Wildcard Usage: This code smell refers to not specifying the version numbers for the build instead using '*' or '+'. The given example in Figure 1 shows that "software.amazon.awssdk:*" has been used. During prototyping or early development, using the wildcard version helps in the fast inclusion of all artifacts from certain groups, but in the long run, this can cause version drift [67], dependency bloat [68], or dependency confusion [69]. This smell is mapped to CWE-829: Inclusion of Functionality from Untrusted Control Sphere.
- Missing Dependency Version: When a dependency is declared without an explicit version number, the build system applies different dependency resolution mechanisms such as Maven will fail the build unless a version is inherited [70], Gradle attempts to resolve the dependency via transitive dependencies [71], potentially introducing unstable or insecure components. This form of version drift is a common software supply chain risk and is covered under CWE-439: Behavioral Change in New Version or Environment and CWE-710: Improper Adherence to Coding Standards.
- Inconsistent Dependency Management: This smell refers to the inconsistency, such as simultaneous use of hardcoded versions and version variables within the same project or using different versions of the same dependency within the same code block. Such inconsistency can result in dependency conflicts and undermine reproducibility. While not directly to a specific CWE, this issue aligns with broader software quality concerns such as CWE-440 Expected Behavior Violation.

IV. SNIFFER: STATIC ANALYTICS TOOL FOR BUILD SCRIPTS

Our static analysis tool, *Sniffer*, has been developed to automatically detect code smells in build scripts. In this section, we describe the development and evaluation process

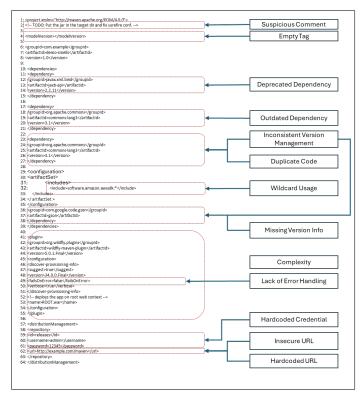


Fig. 1. An annotated Maven script example with all identified code smell categories.

of Sniffer's smell detection. Our tool will be available upon request.

A. Design and Development of Sniffer

Sniffer is a static-analysis tool that detects security and maintainability-oriented code smells in four widely-used build systems: Maven, Gradle, CMake, and Make. The following paragraphs describe each layer in turn.

1. Input Orchestration: On invocation, the dispatcher determines the target build system by (i) examining the file name and (ii) applying lightweight lexical heuristics, for example, searching the first kilobyte for <code>cmake_minimum_required</code> or the presence of make-style rules. The file is then forwarded to the corresponding parser module.

2. Specialised Parsers:

Maven. POM files are loaded as raw bytes, any editor-added line prefixes are stripped, and the payload is parsed with *lxml.XMLParser(recover=true)*. The resulting tree is normalized into lists of dependencies, plugins, and XML nodes used by downstream checks.

Gradle. A tri-regex strategy extracts dependency declarations in Groovy DSL, Kotlin DSL, and map notation; repository URLs are captured via a dedicated pattern. The full script is preserved in raw_content for textual analyses.

CMake. The parser identifies *find_package*, *add_executable*, and *add_library* directives and records their arguments. Files lacking an explicit *cmake_minimum_required* state-

ments are still analyzed, improving coverage of legacy projects.

Make. To avoid side effects, files containing \$(shell ...) fall back to a nave line scanner that collects variable assignments, rules, and commands. Otherwise, the parser exploits make-pn to obtain an expanded database, which is then converted into a structured MakefileAnalysis object.

Details of each parser pattern and regex are provided in appendix.

- 3. Shared Utility Layer: Common functionality is consolidated in common/. In particular, version_utils.py performs metadata look-ups on Maven Central and implements semantic-version comparison. Results are cached in an LRU store to bound network overhead.
- 4. Dynamic Rule Engine: All smell detectors are defined as functions whose names begin with check_ and that accepts exactly one positional argument. At start-up the engine introspects every security-check module, registers the matching callables, and executes them in sequence. Each detector returns a set of issue dictionaries of the form {smell_id,issue,severity}; exceptions are captured and re-emitted as Low-severity findings, ensuring that individual failures do not interrupt analysis.

Smell Catalog: Forty-two detectors are currently implemented. They span version-related risks (missing, inconsistent, outdated, or stale dependencies), hard-coded secrets and absolute paths, insecure transport (HTTP URLs), duplicate or unused declarations, complexity heuristics, and inadequate error handling. All smells are mapped to relevant CWEs to facilitate security triage.

Extensibility: Supporting an additional build system entails providing (i) a parser that emits the canonical data schema and (ii) optional smell detector modules. The dispatcher and rule engine remain untouched, offering a clear path for future expansion (e. g. Bazel or SCons).

In summary, *Sniffer* combines tolerant parsing with a deterministic, modular rule engine, delivering reproducible static analysis across heterogeneous build automation ecosystems while remaining straightforward to extend and maintain.

B. Performance Evaluation

In this section, we discussed the steps of Sniffer's performance evaluation. We evaluated our tool's performance in two ways. i) Evaluation Against Manual Analysis ii) Evaluation Against Oracle Dataset explained below. The results of both analyses are discussed in Section IV-C.

1) Evaluation Against Manual Analysis:

To test Sniffer's performance, we first randomly selected 100 scripts collected from four datasets. Next, two authors manually analyzed the scripts for each of the identified code smells. We then ran Sniffer on the same sampled build scripts and measured the Precision and Recall values by comparing Sniffer's output with our manual analysis to evaluate the tool's performance. Our findings are presented in Table III.

2) Evaluation Against Oracle Dataset: We constructed the Oracle dataset using a closed coding approach [72], where a rater analyzes material and identifies code smells based on a predefined codebook. The dataset consists of 72 scripts that were manually examined for code smells. Raters applied their knowledge of programming and build scripts to determine whether a particular smell was present in each script. To avoid bias, we did not include any raters as part of the primary code smells identification or development Sniffer. The smell identification tasks were performed through Qualtrics. In each task, a rater determined which of the code smells identified in Section III were present in a given script. We recruited 20 Computer Science graduate students who have some level of familiarity with build scripts to serve as raters. We obtained an institutional review board (IRB) approval for student participation VII. Each rater was compensated with a \$20 gift card for their involvement. The 72 scripts were sampled to include a mix of scripts with and without code smells. These scripts were then distributed among the 20 raters, ensuring that each script was independently reviewed by at least two raters, with no rater reviewing more than eight scripts. We observe agreements on the scripts, with a Cohen's Kappa of 0.63. According to Artistein and Poeisio's interpretation [73], the reported agreement is "substantial". After the construction of the Oracle dataset, we evaluated the Sniffer's performance against Oracle using Precision and Recall scores.

C. Performance Evaluation Results

Sniffer's performance for Precision and Recall scores is presented in Table III. As shown in the table, the precision and recall values of the developed tool were measured against the manual analysis, which served as the ground truth. Additionally, we evaluated the tool against the oracle's output by measuring precision and recall across four types of build scripts: Maven, Gradle, Cmake, and Make. When compared against manual analysis, the Sniffer achieved an average precision of 0.92 for Maven and a highest recall of 0.89 for Cmake, indicating reasonably high agreement with ground truth. In terms of performance analysis against Oracle, Maven showed the highest precision (0.84) and highest recall (0.83). Overall, Sniffer's performance analysis with manual analysis scored slightly higher than Oracle's output, indicating similar results. These results demonstrate that the Sniffer is both precise and reliable across multiple build systems, with a strong recall performance when evaluated against both datasets, underscoring its potential for automated detection of code smells in build scripts.

V. EMPIRICAL ANALYSIS OF BUILD SCRIPTS

A. RQ2: How frequently do code smells occur in build scripts?

1) Dataset: In this phase of the study, we conducted a large-scale empirical study with a large-scale dataset of Maven, Gradle, CMake, and Make scripts. To examine the prevalence of identified code smells and enhance the generalizability of our results, we focused on GitHub repositories,

TABLE III SNIFFERS PRECISION AND RECALL

	Manual A	nalysis	Oracle			
Build Scripts	Precision	Recall	Precision	Recall		
Maven	0.92	0.83	0.84	0.83		
Gradle	0.90	0.89	0.81	0.81		
Cmake	0.91	0.93	0.82	0.81		
Make	0.83	0.86	0.83	0.80		
Average	0.89	0.88	0.83	0.81		

TABLE IV SUMMERY OF COLLECTED REPOSITORIES

Attributes	Values							
Script Type	Maven	Gradle	Cmake	Make				
Repositories	913	634	443	2887				
Files	918	634	443	3887				
Total LOC	125502	30872	23679	636283				

which are widely used by organizations to host prominent open-source software (OSS) projects [74]. In alignment with established research practices [75], we curated the collected OSS repositories to have diverse and accessible datasets. The curation process was followed by a set of pre-defined inclusion criteria, detailed as follows:

- Criteria 1: The repository should contain at least one
 of the selected types. The Repositories should contain any of the following types pom.xml, build.gradle,
 build.gradle.kts, Cmake.txt or Makefile.
- Criteria 2: The repositories are not a clone or duplicate. To avoid redundancy, repositories that have already been processed and recorded in a central Google Sheet in Section III-A2 data collection were skipped. This automated approach allowed us to collect a large and diverse set of build scripts from GitHub, forming a strong basis for our empirical study and subsequent evaluation of our static analysis tool. We answer RQ2 using 5882 scripts collected from 913, 634, 443, and 2887 repositories, respectively, for Maven, Gradle, CMake, and Make. Summary attributes of the collected repositories are listed in Table IV. Since most repositories contained only a single build script, the total number of build scripts collected is approximately equal to the number of repositories for Maven, Gradle, and Makefiles. Moreover, given the longstanding use of Makefiles in software development, the majority of the collected data consisted of Makefiles.

B. Answer to RQ2: How frequently do code smells occur in build scripts?

1) Occurrence: The occurrence is the number of each code smell across different build systems. As represented in Table V, among all smells, Wildcard Usage was the most frequent, with 2,205 instances in Make scripts. Insecure URLs followed, especially common in Maven (854) and Make (587). Lack of Error Handling also stood out in Make (988), while Inconsistent Dependency Management was largely observed in Maven (797).

Hardcoded Paths/URLs appeared frequently in Make (664) and Maven (373), and Suspicious Comments were notable in Make (685) and Gradle (104). Deprecated Dependencies were dominant in Gradle (217), and Outdated Dependencies in Maven (319). Duplicate entries were mostly found in Maven (139) and Gradle (116), with none in Make.

Other smells like Hardcoded Credentials, Missing Dependency Version, and Complexity also showed varying occurrences, with Make and Gradle scripts often reporting higher counts. The "no smells" represents the number of scripts where no code smell was found for that certain build type. These patterns suggest that certain smells are more prevalent in specific ecosystems, possibly due to differing development practices or code structure.

2) Proportion of script:

- Approach: The proportion of scripts metric indicates the prevalence of a smell across individual scripts [21]. This metric reflects the percentage of scripts that contain at least one occurrence of smell.
- Results: As presented in Table V, Insecure URLs appeared in the highest proportion of scripts, up to 93% in Maven and 15.1% in Make, underscoring their widespread presence and associated security risks. Wild-card Usage was also highly prevalent, particularly in Make (56.7%) and CMake (23.3%), suggesting potentially ambiguous dependency declarations. In contrast, Hardcoded Credentials were rare, occurring in only 0.9% of Gradle scripts and in less than 0.1% across other script types.

3) Smell Density:

• Approach: In previous studies, researchers utilized vulnerability density [76] and defect density [77], [78] to measure the prevalence of such problems. In line with the same concept, we employed equation 1 to quantify the density of a code smell (*d*). Here, *x* is the total occurrence of code smell for every 1000 Lines Of Code (LOC), represented by KLOC.

Smell Density(d) =
$$\frac{\text{Total occurrences of x}}{\text{KLOC}}$$

Where KLOC= LOC/1000

• Results: The Smell Density (per KLOC) column in Table V reports the frequency of security smells normalized per thousand lines of code (KLOC). Smell density provides a relative measure of smell intensity. Gradle scripts exhibited notably higher smell densities across several categories, such as Deprecated Dependencies (7.029 per KLOC), Duplicate (3.757), and Suspicious Comments (3.369), suggesting these scripts are often smaller but more smell-prone per unit of code. Conversely, Make scripts, while having high absolute occurrences, showed lower density for most smells (e.g., Outdated Dependencies: 0.030 per KLOC), indicating their higher LOC base dilutes the relative impact of smells. This highlights the importance of using density alongside raw counts for fair cross-tool comparisons.

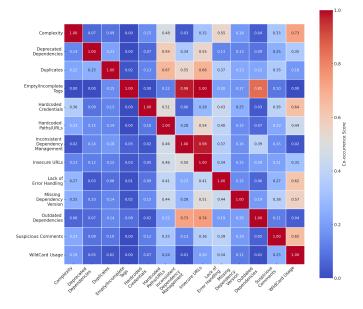


Fig. 2. Heatmap Of Code Smell Co-Occurrence In Build Scripts

4) Smell co-occurrence matrix::

• Approach: To investigate how often one code smell is present with another code smell in build scripts, we performed a pairwise co-occurrence analysis. We calculated the percentage of each smell type cs_i with another smell type cs_j across our dataset of build scripts. Following the methodology proposed by the previous studies [79], [80], we measured the co-occurrence by using the following formula:

Co-occurrence
$$_{cs_i \to cs_j} = \frac{|cs_i \cap cs_j|}{|cs_i|}$$
 where, $i \neq j$

The equation, $|cs_i \cap cs_j|$ represents the number of build scripts that contain both smell types cs_i and cs_j , and $|cs_i|$ denotes the total number of scripts containing cs_i . This directional metric captures the likelihood that the presence of smell cs_i implies the presence of smell cs_j , enabling the identification of strongly associated smell pairs. Notably, Co-occurrence $cs_i \rightarrow cs_j \neq Co$ -occurrence $cs_j \rightarrow cs_i$ due to the asymmetry of the denominator.

Results: As shown in the Figure 2, the code smell cooccurrence in build scripts has several strong associations between specific pairs of smells. Empty/Incomplete Tags exhibit perfect co-occurrence with Insecure URLs (1.00) and a near-perfect association with Inconsistent Dependency Management (0.98), indicating that structurally deficient scripts often suffer from insecure configurations and poor dependency practices. Similarly, Duplicates cooccur frequently with both Hardcoded Paths/URLs (0.67) and Insecure URLs (0.68), suggesting that redundancy in script elements is commonly linked with insecure or non-modular path specifications.

TABLE V Summarization of Smell Occurrences, Smell Density, and Proportion of Scripts for the Four Build Types

	Occurance			Smell Density (per KLOC)			Proportion of Script (%)					
Code Smell Name	Maven	Gradle	Camke	Make	Maven	Gradle	Camke	Make	Maven	Gradle	Camke	Make
Hardcoded Credentials	8	47	3	217	0.064	1.522	0.127	0.341	0.009	0.074	0.007	0.056
Hardcoded Paths/URLs	373	279	25	664	2.972	9.037	1.056	1.044	0.406	0.440	0.056	0.171
Deprecated Dependencies	95	217	11	13	0.757	7.029	0.465	0.020	0.103	0.342	0.025	0.003
Outdated Dependencies	319	87	18	19	2.542	2.818	0.760	0.030	0.347	0.137	0.041	0.005
Inconsistent Dependency Management	797	19	0	0	6.350	0.615	0.000	0.000	0.868	0.030	0.000	0.000
Duplicate	139	116	19	0	1.108	3.757	0.802	0.000	0.151	0.183	0.043	0.000
Missing Dependency Version	121	24	41	278	0.964	0.777	1.731	0.437	0.132	0.038	0.093	0.072
Suspicious Comments	114	104	28	685	0.908	3.369	1.182	1.077	0.124	0.164	0.063	0.176
Insecure URLs	854	123	27	587	6.805	3.984	1.140	0.923	0.930	0.194	0.061	0.151
Empty/Incomplete Tags	41	0	0	0	0.327	0.000	0.000	0.000	0.045	0.000	0.000	0.000
Lack Error Handling	303	4	25	988	2.414	0.130	1.056	1.553	0.330	0.006	0.056	0.254
Complexity	11	99	37	504	0.088	3.207	1.563	0.792	0.012	0.156	0.084	0.130
Wildcard Usage	9	142	103	2205	0.072	4.600	4.350	3.465	0.010	0.224	0.233	0.567
No smells	34	177	251	1151								

VI. DISCUSSION

In this section, we discuss recommendations to mitigate code smells in the build script, the implementation of Sniffer, and future work.

A. Mitigation Strategies

The identification of recurring code smells within build scripts highlights key areas where software quality, maintainability, and security can be significantly improved. In this section, we discuss and recommend strategies to mitigate each of the identified code smells.

Hardcoded Credentials To mitigate this issue, developers should adopt secure credential management practices, such as utilizing dedicated secret management systems (e.g., AWS Secrets Manager or environment variables). Secrets must never be directly stored in scripts or repositories. Scan repositories for exposed secrets using tools like TruffleHog, Gitleaks, or GitHub Secrets can help in secret leakage mitigation. In addition, credential scanning tools, such as *Sniffer*, can automate the detection and remediation of hardcoded credentials.

Hardcoded Paths and URLs Mitigation involves replacing absolute paths and URLs with relative paths, environment variables, or centralized configuration files. Such practices enhance portability and adaptability across diverse development environments and reduce security risks [81].

Deprecated Dependencies: Regular dependency monitoring and automated tools such as OWASP Dependency-Check or utilizing Software composition analysis (SCA) should be employed to identify deprecated or unmaintained libraries. The software development team should proactively replace deprecated dependencies with supported alternatives to minimize security risks [82].

Outdated Dependencies: Unused dependencies, redundant features, components, files, and outdated documentation should be systematically removed to reduce maintenance overhead and potential security risks [83]. Continuous dependency monitoring, along with the use of automated update tools such as Dependabot and Renovate, can help mitigate risks with outdated libraries. Furthermore, maintaining a disciplined

update policy aids in the timely application of security patches. Enabling automated pull request notifications may enhance more frequent and consistent dependency upgrades [84].

Duplicates: Mitigating duplicate declarations involves regular dependency audits and leveraging build tools (e.g., Maven's dependency analysis plugins) to detect redundancy. Clean, simplified dependency structures enhance maintainability and reduce complexity.

Suspicious Commenst: Developers should adopt clear coding standards discouraging inactive commented-out code and establish regular peer-review practices to remove ambiguous comments promptly. Furthermore, establishing clear guidelines on the types of information that should be included in code comments and enforcing these guidelines through code reviews can enhance coding standards [21].

Insecure URLs: Mitigating this involves enforcing HTTPS protocols for all external connections within build scripts. Automated scanning tools can continuously check build scripts for insecure HTTP links, thus preventing man-in-the-middle vulnerabilities.

Empty/Incomplete Tags To mitigate empty tags or elements, automated validation tools (e.g., XML schema validators) should be integrated into CI/CD pipelines. Adherence to XML schema standards prevents unintended behavior and enhances script clarity.

Complexity: To address complexity in scripts, development teams should adopt clear coding conventions and modularize build logic into reusable components or scripts. Regular refactoring sessions and peer reviews help manage complexity, making build scripts easier to audit and maintain.

Lack of Error Handling: Lack of Error Handling is concerning in automated build environments where early detection and halting failure are essential to maintaining software quality. Continuing execution after an error may lead to partially configured systems or incomplete dependency states, increasing the risk of introducing latent vulnerabilities. To address this, concrete error-handling policies within build scripts are needed. A recommended mitigation strategy involves configuring plugins to fail explicitly upon

encountering errors (e.g.,<onError>fail</onError> and <failOnError>true</failOnError>). In addition, enforcing a fail-fast mechanism can help [85]. This approach not only aligns with recommended practices in continuous integration and DevSecOps but also supports reproducible and verifiable builds [86].

Wildcard Usage: A wildcard dependency may be helpful in the early phase of software development, but it has downsides as the project progresses. While wildcards ensure that dependencies are always up-to-date, they also introduce risks by pulling in potentially unstable or breaking changes without proper review [87]. Dependency versions should be explicitly specified or use a floating range. Employing lock files and version pinning would enhance reproducibility and secure builds by preventing uncontrolled upgrades.

Missing Dependency Version: Version specifications need to be explicit to prevent unexpected dependency drift. Explicit dependency management, including the practice of version pinning and locking files (e.g., Maven's dependency-lock plugin), keeps the system consistent and helps in establishing reproducible builds.

Inconsistent Dependency Management: Adopting consistent version management through standardized properties, dependency management tools (e.g., Maven's BOM feature), and unified policies significantly reduces inconsistency and simplifies dependency updates [88].

B. Implications of Findings

Our findings have several practical implications. First, the prevalence of security-related smells (e.g., hardcoded secrets and insecure URLs) suggests a need for greater security awareness during build script development. Second, the presence of maintainability-related smells, such as missing version information and inconsistent dependency management, points to the need for improved tooling and standardization practices. Organizations can adopt our tool as part of code review to enforce best practices. Moreover, the detection of smells across open-source repositories indicates that these issues are widespread, underlining the need for ecosystem-wide adoption of static analysis tools, such as Sniffer, to build systems for better maintainability and reduce technical debt.

C. Future Work

While our work lays the foundation for detecting code smells in build scripts, several directions remain for future research. To enhance the tool's detection capabilities, techniques such as machine learning or natural language processing could be integrated to improve its accuracy, especially for context-sensitive or semantically subtle smells. Incorporating contextual information such as project maturity, domain, or deployment environment can help prioritize smells based on impact and relevance. Expanding the tool's applicability to other build systems and configuration files, such as Bazel or Ant, would broaden its utility.

VII. ETHICAL CONSIDERATION

This study involved the analysis of publicly available opensource build scripts collected from GitHub. No private or personally identifiable information (PII) was accessed or used. All data was handled in compliance with the platform's terms of service and policies [89]. We also obtained institutional review board (IRB) approval for our user study. All data was collected, handled, and stored in institutional secure storage. Our goal is to support the broader software engineering community in improving build quality and security.

VIII. THREATS TO VALIDITY

In this section, we acknowledge and discuss the limitations of our research findings:

Conclusion Validity: The identification and classification of code smells in build scripts involved subjective judgment. The initial extraction, categorization of smells, and mapping to CWEs were performed manually by the authors, introducing potential subjectivity. Different researchers might classify the same code differently based on their experience and perspectives. However, to overcome the obstacle, we followed a systematic way to validate our findings by multiple authors involved in the coding and resolved the disagreement by following established guidelines [53].

Internal Validity: We acknowledge the possibility of other code smells existing within build scripts that were not identified in our study. To mitigate this threat, we analyzed 2134 build scripts across Maven, Gradle, Make, and Cmake; additional or context-specific smells may remain undiscovered. In the future, we aim to expand our research by expanding the dataset and exploring additional scripting contexts to enhance the comprehensiveness of identified smells. The detection accuracy of the developed tool is dependent on heuristic-based rules and patterns defined during tool development. These heuristics could produce false positives and false negatives. To address this, we iteratively refined our heuristics through continuous testing against manually validated scripts.

External Validity: Our findings are subject to limitations in external validity, as the results may not be generalizable beyond the studied build scripts. The tool is specifically developed for certain build script types, and thus, findings might not be directly extended to other build systems with different syntactic or semantic structures. Furthermore, the evaluation was conducted exclusively on open-source build scripts obtained from GitHub repositories. The prevalence and impact of the identified code smells may vary in proprietary or enterprise environments, where development practices, quality standards, and tooling ecosystems differ.

IX. CONCLUSION

Build scripts automate the process of creating a deployable application. As systems grow in scale and complexity, these scripts become harder to maintain, affecting project quality and developer productivity. Code smells indicate some recurring coding patterns that occur frequently. Though it may not always have negative effects, a code smell should still be taken

seriously because it could be a sign of future security and maintainability risk. In this study, we performed an analysis of code smells in build scripts through a mixed-methods approach combining qualitative issue analysis and large-scale static analysis. By analyzing 5,882 build scripts from Maven, Gradle, CMake, and Make across 4227 open-source GitHub repositories, we identified 13 categories of code smells, totaling 10,895 occurrences. Our findings highlight that certain smells, such as insecure URLs, hardcoded paths/urls, and wildcard usage, are particularly prevalent across specific build systems. Furthermore, the co-occurrence analysis revealed strong associations among specific smell pairs, suggesting the presence of systemic patterns in configuration practices. These insights underscore the need for improved tooling and development practices to detect and address code smells in build automation scripts. To support this, we proposed mitigation strategies aimed at improving the quality, maintainability, and security of build processes in modern software engineering.

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