

SoK: Automated Vulnerability Repair: Methods, Tools, and Assessments

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Abstract

The increasing complexity of software has led to the steady growth of vulnerabilities. *Vulnerability repair* investigates how to fix software vulnerabilities. Manual vulnerability repair is labor-intensive and time-consuming because it relies on human experts, highlighting the importance of *Automated Vulnerability Repair (AVR)*. In this SoK, we present the systematization of AVR methods through the three steps of AVR workflow: vulnerability analysis, patch generation, and patch validation. We assess AVR tools for C/C++ and Java programs as they have been widely studied by the community. Since existing AVR tools for C/C++ programs are evaluated with different datasets, which often consist of a few vulnerabilities, we construct the first C/C++ vulnerability repair benchmark dataset, dubbed VUL4C, which contains 144 vulnerabilities as well as their exploits and patches. We use VUL4C to evaluate seven AVR tools for C/C++ programs and use the third-party VUL4J dataset to evaluate two AVR tools for Java programs. We also discuss future research directions.

1 Introduction

The number of software vulnerabilities has been growing rapidly. For example, in 2023 alone, 30,927 vulnerabilities are added to the *National Vulnerability Database (NVD)*, and a majority of them are critical [97]. The large number of vulnerabilities on an annual basis highlights the importance of *Automated Vulnerability Repair (AVR)*, which aims to fix vulnerabilities while minimizing, if not completely eliminating, the reliance on domain experts.

In principle, AVR is a special case of *Automated Program Repair (APR)* because the latter aims to fix software defects that include *security defects* (i.e., vulnerabilities) and *functional defects* (i.e., non-vulnerabilities). It is known that an APR technique may not be an effective AVR technique [94, 128] or even applicable to AVR (e.g., the statistical fault localization technique [3]).

The status quo of AVR can be summarized as follows. First, the most closely related prior study is an independent and concurrent SoK [59], which focuses on the *patch generation* step of the AVR workflow, but not the entire AVR workflow. Moreover, their empirical analysis [59] focuses on four patch generation methods [38, 49, 52, 148] for C/C++ programs via two vulnerability datasets [38, 106], leaving other AVR tools unaddressed. Second, there are surveys on APR that also briefly discuss AVR [39, 47, 77] and on learning-based AVR [150]. However, these surveys do not deal with the entire AVR workflow or other approaches to AVR. Third, there are many empirical studies, such as: [8, 94, 128] analyze the effectiveness of APR tools; [145] analyzes the effectiveness of pre-trained models for vulnerability repair; and [64, 93] analyze the effectiveness of *Large Language Model (LLM)* for vulnerability repair. However, these studies do not consider AVR tools. Fourth, there is neither a benchmark nor a unified assessment process for evaluating AVR tools geared towards C/C++ programs because existing studies either use their own datasets [14, 34, 38, 49, 103, 148, 151] or use their own evaluation methods, making it infeasible to compare their results (e.g., some evaluation methods require testing patch validity [38, 49, 103, 148] while others do not [14, 34, 151]). The unsatisfying status quo motivates the present SoK.

Our contributions. This paper makes four contributions. First, we systematize the problem of, and existing solutions to, AVR. We systematize AVR through its three steps of workflow: *vulnerability analysis*, *patch generation*, and *vulnerability validation*. The systematization leads to a number of insights, such as: (i) existing *vulnerability analysis* methods cannot accurately localize vulnerabilities; (ii) template-based *patch generation* methods perform well on specific types of vulnerabilities but lack general applicability; (iii) static analysis-based *patch validation* methods incur high false-negatives due to their limited rules and the path explosion problem of symbolic executions.

Second, to enable fair comparison between AVR tools, we create the first C/C++ vulnerability repair benchmark dataset, dubbed VUL4C, which contains 144 vulnerabilities associ-

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ated with 23 software products and 19 *Common Weakness Enumeration* (CWE) types [76]. When compared with previous datasets, VUL4C has two features: (i) it provides exploits, vulnerable programs, patches, and methods for triggering vulnerabilities; (ii) it covers a broader range of vulnerabilities, software, and vulnerability types. VUL4C represents a new baseline for AVR research and is available at <https://doi.org/10.5281/zenodo.15609776>.

Third, we apply VUL4C to evaluate seven AVR tools for C/C++ programs and apply the existing VUL4J dataset to evaluate two AVR tools for Java programs. Our findings include: (i) semantics-based AVR tools outperform learning-based ones in generating high-quality patches; (ii) learning-based AVR tools lack rigorous evaluation methodologies; (iii) the plausible patches generated by semantics-based *patch generation* methods cannot fix the corresponding vulnerabilities but can assist developers in addressing vulnerabilities.

Fourth, the preceding findings inspire us to propose a research roadmap towards tackling the AVR problem. The roadmap highlights the importance of developing effective vulnerability analysis techniques to serve as a foundation of patch generation and developing automated vulnerability validation techniques.

As a side product, we apply VUL4C to evaluate two APR tools for C/C++ programs and the third-party VUL4J to evaluate two APR tools for Java programs. We find: (i) APR models with a stronger code comprehension capability perform better in patch generation, and leveraging multiple models together can perform even better; (ii) APR models employing detailed thought processes in CoT achieve a higher patch generation capability, while lacking vulnerability information causes repair failures.

Paper Outline. Section 2 describes our systematization methodology. Section 3 systematizes automated vulnerability analysis. Section 4 systematizes automated patch generation. Section 5 systematizes automated patch validation. Section 6 presents VUL4C. Section 7 describes our empirical study. Section 8 discusses future research directions. Section 9 concludes the paper.

2 Systematization Methodology

2.1 Terminology and Scope

Terminology. We use the following standard terms [39, 106]. A *test case*, or *test suite*, is often prepared by a software developer to verify whether a program meets its specification. A test case that meets the specification is called a *positive case*; otherwise, it is a *negative case*. An *exploit* is an input that leads to the compromise a security property. A *vulnerability location* is the lines of code (or statements) where a vulnerability resides; a *vulnerability fix location* refers to the lines of code that need to be modified in order to fix a vulnerability; these two locations may or may not be the same

(see examples in Appendix A). A *candidate patch* is a patch that has yet to be validated, meaning it may or may not be valid; a *plausible patch* is a candidate patch that has been validated from a security perspective, but may not truly fix a vulnerability because patch validation may not be thorough enough (e.g., only considering a few test cases) [121].

Scope. We focus on AVR, which often takes the output of a vulnerability detection tool as input. Although AVR is a special case of APR, the literature does not always distinguish them [39, 47, 77, 78], perhaps because some APR techniques can be leveraged for AVR purposes, as shown in the present paper. Nevertheless, the following three aspects highlight the difference between APR and AVR.

- **Purpose.** AVR deals with vulnerabilities that can be exploited to compromise security properties. APR deals with software defects that make programs behave unexpectedly but may not be exploited to compromise security properties.
- **Input.** AVR often takes one exploit as input for triggering and validating a vulnerability, where the input is often obtained via fuzzing and often difficult to translate into test cases that are required by APR [106]. Whereas, APR often takes as input a set of positive and negative test cases, which are crafted by human developers to localize defects and validate correctness of repaired programs.
- **Analysis.** AVR often starts with an analysis to localize vulnerabilities (e.g., via the violated security constraints [38, 49] or exploitation behaviors [106]) and then generates patches (e.g., by resolving the violated security constraints [103] or by leveraging exploitation behaviors [151]). The analysis is often specific to vulnerability types, as different types exhibit different characteristics. On the other hand, APR is geared towards repairing the functionality of a program, which is orthogonal to security properties.

The preceding discussion highlights that APR solutions are not sufficient for AVR purposes, and thus the community should treat AVR as a separate research problem.

2.2 AVR Workflow

Figure 1 depicts the AVR workflow in three steps: automated vulnerability analysis, automated patch generation, and automated patch validation, which are highlighted below and elaborated in subsequent sections.

Automated vulnerability analysis. This step takes a vulnerable program as input (e.g., the output of a vulnerability detector), analyzes the vulnerable program, and outputs useful vulnerability characteristics (e.g., vulnerability type, violated security property, root cause, vulnerability location, fix location). There are four approaches to automated vulnerability analysis: (i) *value-flow analysis*, which tracks the propagation of data and control in a program; (ii) *formal analysis*, which leverages mathematical modeling and logical reasoning; (iii) *symbolic execution*, which replaces program variables with symbolic expressions and systematically explores execution

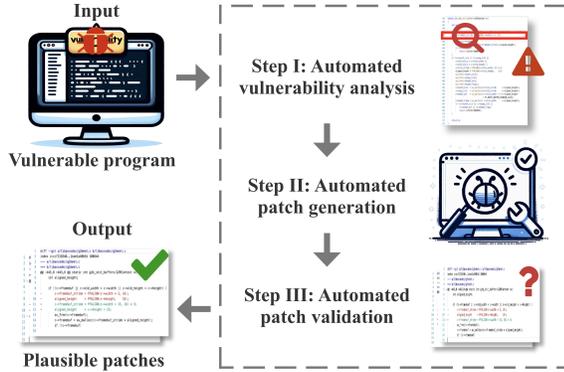


Figure 1: AVR workflow (three steps)

paths; (iv) *statistical analysis*, which leverages statistical features to identify correlations.

Automated patch generation. This step generates one or multiple *candidate patches* for a given vulnerability. There are four approaches: (i) *search-based*, which searches candidate patches in a pre-defined patch space; (ii) *template-based*, which leverages abstract patch templates; (iii) *semantics-based*, which leverages program semantics; and (iv) *learning-based*, which leverages deep learning.

Automated patch validation. This step determines the validity of a candidate patch generated in the preceding step, rejecting or validating it as a *plausible patch*. There are two approaches to patch validation: (i) *static analysis-based*, which verifies a candidate patch without executing the patched program; (ii) *dynamic analysis-based*, which executes a patched program with the exploit and test cases in question (if available) and observes the program’s runtime behavior.

2.3 Identifying AVR Literature

We use Google Scholar to search for papers published in the CORE2023 A/A* conferences [29] or top-tier journals (TDSC, TIFS, TSE, TOSEM, ESE, TC) between 2000 and 2024 using the following eight keywords: *vulnerability repair*, *vulnerability fix*, *vulnerability patch*, *vulnerability patch generation*, *vulnerability fix generation*, *automated vulnerability repair*, *automated vulnerability fix*, and *automated vulnerability patch*. For each keyword, we consider the first 100 entries ranked by relevance given by Google Scholar. This leads to 800 papers for our manual examination based on their technical relevance, which results in 32 papers, including: (i) 27 papers that present 27 AVR tools, respectively; (ii) five empirical studies on vulnerability repair.

For each of the 32 papers, we use the snowballing approach [125] (as in [67]) to identify other relevant papers published in CORE2023 A/A* conferences [29] or top-tier journals, leading to 38 additional papers that present 37 AVR tools and one empirical study. In total, we obtain $32 + 38 = 70$ papers

for systematization, including 64 AVR tools and six empirical studies. Figure 2 highlights the 64 AVR tools in terms of their workflow. Table 1 compares the 64 AVR tools via attributes that will be described in Sections 3-5.

3 Automated Vulnerability Analysis

3.1 Value-flow Analysis

This approach employs code analysis tools (e.g., Joern [138]) to generate program representations, such as *Control Flow Graphs* (CFGs) and *Data Flow Graphs* (DFGs), and then analyzes these graphs to infer violations of security properties and localize vulnerabilities. This approach is type-sensitive as different vulnerability types require different inference rules.

There are 13 methods in this approach. (i) LeakFix [36] and MemFix [55] leverage CFGs to analyze allocation/deallocation states of objects and identify memory leaks. (ii) IntPTI [16] and IntPatch [143] analyze types and value ranges of expressions to identify potential integer errors. (iii) ContractTinker [120] uses program slices to generate contextual dependency graphs and extract vulnerable code snippets. (iv) SMARTSHIELD [149] analyzes control flows and data manipulations to derive bytecode-level control flow and data flow dependencies for matching vulnerability patterns. (v) Rupair [46] traces data flows (from allocation points to usage points) to recognize buffer overflow vulnerability paths. (vi) FixMeUp [109] analyzes data flow and control flow dependencies via interprocedural program slicing, and then uses them to recognize missing access control logic and extract *Access Control Templates* (ACTs). (vii) SkyPort [107] employs static value-flow analysis to extract the semantic logic of vulnerability injection. (viii) [105] identifies unsafe library functions via control-flow, data-flow, and pointer analysis. (ix) CIntFix [17] identifies (tolerable) C integer errors by leveraging the shortest-path from each node to a security-critical node in the use-def graph. (x) Elysium [32] uses taint analysis to conduct bytecode-level value-flow analysis and infer the context needed by vulnerability patching. (xi) SAVER [44] uses the *Object Flow Graph* (OFG) to track the event flow of heap objects and identify memory error patterns and their associated code paths. (xii) RLFixer [117] tracks propagation paths of resource objects to identify how they escape the context of their creation methods. (xiii) AutoPAG [63] uses static dataflow-based backward taint propagation to identify the statements that cause out-of-bounds vulnerabilities.

This approach often incurs prohibitive computational overheads because tracking value propagation in complex programs can lead to an exponential path growth, and often fails to accurately parse and/or analyze code.

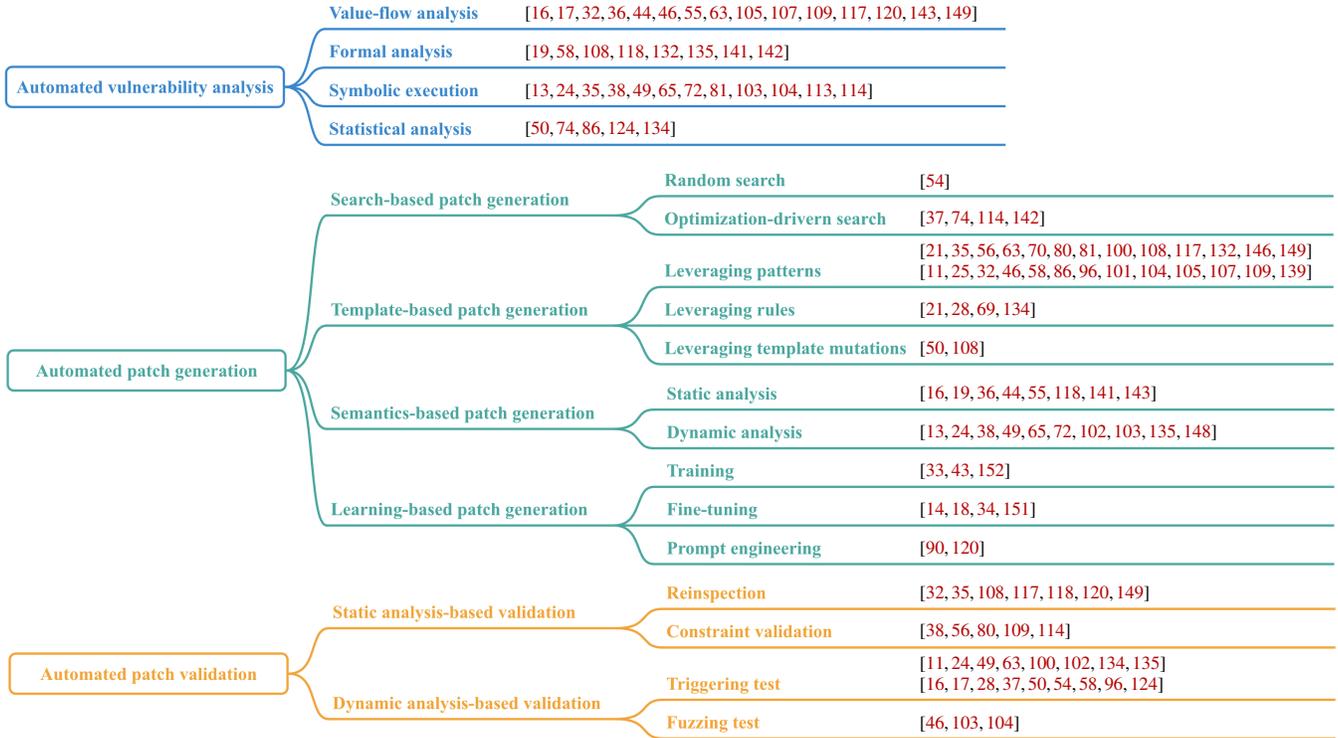


Figure 2: Characterizing the 64 AVR tool through AVR workflow: vulnerability analysis, patch generation, and patch validation

3.2 Formal Analysis

This approach uses formal analysis [126] to identify the security properties that are violated and determine unsafe program states. There are seven methods in this approach. (i) Remedy [19] constructs a semantic model of regex to identify potentially unsafe states, while using *Deterministic Finite Automaton* (DFA) to represent violations of security properties and assist patch synthesis. (ii) [141] uses DFA to model web application inputs and identify potential code injection. (iii) TAPFixer [142] uses model checking to determine whether security properties hold. (iv) VULMET [135] reasons the weakest precondition to convert patch-incurred changes into hot patch constraints. (v) SmartFix [108] uses a formal verification tool, VeriSmart [53], to perform mathematical proofs on contracts, while using regression detection assertions to generate patch verification conditions. (vi) FootPatch [118] uses Separation Logic [92] to model program heap states and uses the Frame Inference technique [5] to detect violations of heap safety properties. (vii) CONCH [132] uses inference rules to localize code triggering null pointer dereference errors.

This approach requires comprehensive modeling and verification of a target program, and thus encounters two challenges: (i) the inherent difficulty in creating accurate models for real-

world programs, and (ii) the potential state space explosion that can render exhaustive verification infeasible.

3.3 Symbolic Execution

This approach uses symbolic variables and constraint solvers to explore program paths, derive path conditions, and identify the input conditions that can trigger vulnerability.

There are 11 methods in this approach. (i) Angelix [72] uses controlled symbolic execution to extract angelic forests (which is a representation of program behaviors) and capture repair constraints associated with suspicious expressions. (ii) Errdoc [113] analyzes vulnerability information related to error handling code. (iii) SymlogRepair [65] uses *Symbolic Execution of Datalog* (SEDL) to describe path constraints related to vulnerabilities. (iv) KARMA [13] performs symbolic execution on both vulnerable functions and candidate functions in parallel to determine whether they are semantically equivalent. (v) Senx [49] uses a hybrid execution engine to run programs at the LLVM IR instruction level and gathers vulnerability information. (vi) OSSPatcher [24] uses a multi-path exploration to extract function-level binary characteristics. (vii) Definery [114] uses symbolic execution to derive path constraints and state effects of smart contracts, and uses symbolic summaries to identify the execution paths that violate

exponential growth of execution paths (incurred by loops, branches, or recursion) forces incomplete exploration, potentially overlooking vulnerabilities; and (ii) complex operations (e.g., cryptographic functions, floating-point arithmetic) often generate constraints that are beyond the reach of current SMT solvers, causing timeouts or false negatives.

3.4 Statistical Analysis

This approach uses statistical features to identify correlations between vulnerability patterns and code characteristics. It then uses these correlations to analyze code, recognize their potential vulnerabilities, and determine their locations. There are three methods in this approach. (i) Exterminator [86] employs randomized heap memory layout and probabilistic canary checks to differentiate buffer overflows and dangling pointer errors to identify the memory operations responsible for these vulnerabilities. (ii) HyperGI [74] uses information entropy to quantify information leakage and uses program slices to locate the information leakage point. (iii) PAR [50], VFix [134], and [124] employ statistical analysis and congestion values [20] for root cause analysis [7, 91, 133] and vulnerability localization.

This approach demands numerous tests for identifying statistical correlations. It often incurs high false-positives because it uses statistical correlations rather than program semantics.

4 Automated Patch Generation

4.1 Search-based Patch Generation

This approach formulates patch generation as a search problem so that code snippets are iteratively modified and recombined to produce candidate patches. It often uses search algorithms (e.g., genetic programming [51]) to identify repairs from typically a vast patch space. Existing methods in this approach can be divided into two categories:

- **Random search.** These methods explore the patch space through random perturbations/mutations, meaning they lack explicit objective functions for optimization. For instance, GenProg [54] iteratively generates program variants via mutation and crossover, evaluates them via test cases, and selects the best-performing variants that pass all tests.
- **Optimization-driven search.** These methods use objective functions (e.g., test pass rate [37] and code quality metrics [74]) to steer the exploration while leveraging heuristic rules or optimization techniques to narrow down the search space. Five methods belong to this category. (i) Fix2Fit [37] uses fuzzing and the test pass rate to refine the partitioning of the patch space. (ii) HyperGI [74] uses a fitness function to balance security and functionality preservation to guide genetic algorithms in generating patches. (iii) Definery [114] uses valid and invalid execution traces to direct

the search. (iv) [124] prunes the search space by discarding the variants that fail all test cases and applying weighted sampling. (v) TapFixer [142] uses negated-property reasoning to perform abstraction-refinement and identify patches.

This approach is largely agnostic to vulnerability types because it mutates code. However, the *random search* methods suffer from a low efficiency incurred by the vast search space with a high likelihood of timeout [8]. The *optimization-driven search* methods encounter two challenges: (i) the search space explosion incurred by the combinatorial complexity of program mutations, and (ii) the patch overfitting that the generated patches can pass the test cases but cannot fix the vulnerability in question.

4.2 Template-based Patch Generation

This approach uses abstract patch templates to synthesize candidate patches, where templates are defined manually or derived from (e.g.) historical vulnerability fixes [70]. Existing methods in this approach can be divided into three categories:

- **Leveraging patterns.** These methods use pre-defined patterns to generate candidate patches. Nine methods belong to this category. (i) BovInspector [35] uses mapping between vulnerable APIs and their secure counterparts to address buffer overflow vulnerabilities. (ii) Rrepair [46] fixes buffer overflows via argument lifting and inserting guards composed of specific statement sequences. (iii) RegexScalpel [58] identifies vulnerable regex patterns to fix ReDoS vulnerabilities. (iv) [105] uses mapping between unsafe library functions and safe functions to prevent buffer overflow vulnerabilities. (v) FixMeUp [109] takes explicit mapping between sensitive operations and correct access-control checks as input. (vi) CONCH [132] leverages three abstract patch templates to conduct NULL pointer checks. (vii) Binary-level repair methods [11, 25, 86] employ pre-defined byte-level patch templates. (viii) Smart contract repair methods [32, 81, 96, 108, 149] use predefined patch templates specific to vulnerability types. (ix) Other methods use their own abstract patch templates, which may be derived from secure coding practices [21, 117, 146] or historical vulnerability patches [56, 63, 70, 80, 100, 101, 104, 107, 139].
- **Leveraging rules.** These methods use pre-defined rules to generate candidate patches, where pre-defined rules are transformation rules or logic rules that typically involve grammatical analysis or check the presence of a statement before applying an abstract patch template. Four methods belong to this category. (i) CIntFix [21] fixes C integer errors by elevating the precision of arithmetic operations according to a set of code transformation rules. (ii) NPEFix [28] uses nine strategies to repair null pointer exceptions. (iii) CDRep [69] defines seven rules to fix cryptographic misuse vulnerabilities. (iv) VFix [134] defines two sets of rules to determine how to add NULL pointer checks and initialization operations under different conditions.

- **Leveraging template mutations.** These methods adapt patch templates to contexts via template mutations. Two methods belong to this category. (i) PAR [50] extracts 10 common fix templates from developer patches, and then mutates these templates to identify high-fitness variants and iteratively generate plausible patches. (ii) SmartFix [108] defines six atomic repair templates for five distinct vulnerability types to produce various combinations of the six atomic repair templates (guided by the number of alarms that are reduced in the validation process).

This approach can generate quality candidate patches for specific types of vulnerabilities. Its effectiveness depends on the quality of the abstract patch templates, and the approach may fail due to its poor adaptability in dealing with abstract patch templates (Appendix B presents two examples to illustrate this adaptability issue). One mitigation to this problem is to design post-processing rules [132].

4.3 Semantics-based Patch Generation

This approach leverages the security constraint(s) violated by a vulnerability to generate a candidate patch that satisfies the constraint(s). Existing methods in this approach rely on either static analysis or dynamic execution of test cases or exploits to identify the security constraint(s) that are violated by a vulnerability. These methods fall under two categories:

- **Static analysis.** These methods [16, 19, 36, 44, 55, 118, 141, 143] use static analysis and repair techniques to generate candidate patches. Methods in this category include: (i) SAVER [44] uses object flow graphs and variable states to construct and solve constraints and generate candidate patches. (ii) FootPatch [118] uses Separation Logic [95] to infer specifications and address memory-related vulnerabilities. (iii) [141] solves constraints inferred from DFA to generate patches for string vulnerabilities in PHP.
- **Dynamic analysis.** These methods [13, 24, 38, 49, 65, 72, 102, 103, 135, 148] often execute test cases or exploits to detect crashes or unstable behaviors. Methods in this category include: ExtractFix [38] uses sanitizer-defined rules to derive crash-free constraints and transform them to candidate patches [71]. (ii) Senx [49] uses expert-defined security properties and concolic execution [98] to identify the security properties that are violated by vulnerabilities, and then generates predicates to synthesize candidate patches. (iii) VulnFix [148] mutates program states to infer patch invariants at potential fix locations, and then uses these invariants to guide the generation of candidate patches.

This approach encounters three challenges: (i) program analysis methods (e.g., symbolic execution) are time-consuming and thus not scalable; (ii) the resulting accuracy depends on the precision of program analysis methods/tools; and (iii) the patch overfitting problem, namely that the resulting patches are only applicable to specific vulnerability types. Note that (iii) may be alleviated via the constraint space

partition technique [102] or using more test cases [148].

4.4 Learning-based Patch Generation

This approach typically uses deep learning or *Large Language Models* (LLMs) to transform vulnerable code into non-vulnerable code. Existing methods in this approach can be divided into three categories:

- **Training.** These methods [33, 43, 152] often use the *Neural Machine Translation* (NMT) technique [111] and demand a sufficient amount of training data, which may not be available in practice. This demand of data may be alleviated by leveraging Generative Adversarial Networks (GANs) [41], as shown in [43], or by encoding vulnerabilities security properties, as shown in [152].
- **Fine-tuning.** These methods involve additional training on top of a pre-trained model, typically by leveraging a smaller, domain-specific vulnerability dataset. Four methods fall under this category. (i) VRepair [14] and SeqTrans [18] use a specialized vulnerability repair dataset to fine-tune a Transformer model [119] trained with a bug fix corpus. (ii) VQM [33] fine-tunes a Vision Transformer model [10] to learn code changes. (iii) VulRepair [34] incorporates pre-trained CodeT5 [123] into AVR to achieve a high repair capability. (iv) VulMaster [151] augments its fine-tuning dataset with CWE knowledge to improve repair accuracy.
- **Prompt engineering.** These methods use carefully crafted prompts to guide LLMs in patch generation. Four methods belong to this category. (i) [93] uses reports from [40] to construct prompts and evaluate LLMs' patch generation capability in zero-shot settings. (ii) PPatHF [90] incorporates human-crafted patches into prompts to guide LLMs in patch generation, in a zero-shot setting. (iii) [64] incorporates historical patches into prompts to assess LLMs in few-shot settings, showing marginal improvement over the results obtained in the zero-shot setting. (iv) Contract-Tinker [120] uses *Chain-of-Thought* (CoT) to guide LLMs in patch generation.

This approach initially adopts APR techniques for AVR purposes without accounting for unique characteristics of vulnerabilities. It is known that accounting for vulnerability-specific characteristics can enhance the quality of the resulting candidate patches [151]. This approach typically addresses vulnerabilities at the function level, which may not be adequate due to the prevalence of cross-function vulnerabilities [60]. Moreover, most learning-based patch generation methods (e.g., [14, 33, 34]) use special tokens to highlight vulnerable statements in the data pre-processing step, allowing the resulting models to generate patches for these specific statements. However, the evaluation of these methods is conducted on the same pre-processed data (e.g., [14, 33, 34]), rendering their usefulness questionable.

5 Automated Patch Validation

5.1 Static Analysis-based Validation

This approach uses static analysis to determine whether a patched program is no longer vulnerable. Existing methods in this approach can be divided into two categories:

- **Reinspection.** These validation methods use static analysis to rescan a program after applying a candidate patch to it. Methods in this category include: (i) Elysium [32] leverages Osiris, Mythril, and Oyente [68] for patch validation. (ii) BovInspector [35] leverages the rules defined by Fortify [89] to validate a patched program. (iii) SmartFix [108] develops a patch verifier on top of VeriSmart [53] for patch validation. (iv) RLFixer [117] re-runs the resource-leak detector on a patched program to ensure that the previously detected leaks have been resolved. (v) FootPatch [118] leverages Infer [30] to validate a patched program. (vi) ContractTinker [120] uses GPT-4 for patch validation. (vii) SMARTSHIELD [149] leverages three state-of-the-art smart contract analysis tools, namely Securify [116], Osiris [115], and Mythril [22], for patch validation.
- **Constraint validation.** These validation methods use SMT to verify that a patched program indeed satisfies the desired security constraints. Methods in this category include: (i) ExtractFix [38] uses SMT to recalculate the satisfiability of security constraints with candidate patches. (ii) NPEX [56], IntRepair [80], and Definery [114] use static symbolic execution to validate patched programs. (iii) FixMeUp [109] uses access control templates and data dependences to identify the missing access control checks.

This approach often incurs high false-negatives because the rules are often limited and symbolic executions often encounter the problem of path explosion (i.e., forcing a limited depth of exploration).

5.2 Dynamic Analysis-based Validation

This approach runs an exploit to confirm that a vulnerability can no longer be triggered. Existing methods under this approach can be divided into two categories:

- **Triggering test.** These validation methods compile a patched program and then run the associated exploit against the resulting executable, such that a failure in compromising the executable means the patch is valid. Methods in this category include: (i) SafeStack [11], and OSSPatcher [24], Senx [49], AutoPaG [63], and VULMET [135] apply a candidate patch to a vulnerable program and retest the patched version via a known exploit. (ii) IntPTI [16], CIntFix [17], NPEFix [28], Fix2Fit [37], PAR [50], Genprog [54], RegexScalpel [58], LeakPair [100], [124], and VFix [134] validate a candidate patch by executing positive and negative test cases to provide a nuanced view of the patch’s effectiveness. (iii) EVMPatch [96] replays attacks

against patched contracts to show the attacks are thwarted.

- **Fuzzing test.** These validation methods conduct more comprehensive security checks on candidate patches. Methods in this category include: (i) Rupart [46] uses the idea of trace validation in fuzzing to check the equivalence between a patched program and its original version to ensure that the patch introduces no additional security or functionality impacts. (ii) CrashRepair [103] and PatchWeave [104] validate a candidate patch via differential fuzzing [42].

This approach is effective in verifying whether a vulnerability has been fixed. However, it cannot guarantee that the patch does not alter the functionality or semantics of the vulnerable program, which demands comprehensive testing. Moreover, this approach is hindered by the availability of exploits, in contrast to APR where adequate test cases are often available.

6 VUL4C: Benchmark Dataset for Repairing C/C++ Vulnerabilities

An AVR benchmark should provide (i) real-world vulnerabilities and their patches and (ii) at least one vulnerability trigger for each vulnerability and the corresponding test reports. Table 2 summarizes existing C/C++ vulnerability datasets, including: (i) two synthetic datasets [88, 94]; (ii) six datasets [6, 12, 31, 82, 83, 122] that lack exploits, making them useful for model training but not for evaluating semantics-based patch generation methods; (iii) two datasets [38, 106] that cover a very small number, and few types, of vulnerabilities; (iv) one dataset, LinuxFlaw [79], that contains 105 patches and five distinct exploit trigger methods, but four of them are not suitable for evaluating AVR because AVR often leverages fuzzing for patch generation [148]. All these datasets, except CB-REPAIR [94], do not include test cases. This highlights the need of benchmark and prompts us to construct one, dubbed VUL4C, via the following four steps.

Step 1: Collecting vulnerabilities. We collect existing datasets [38, 79, 104, 106], including their associated exploits. Since Senx [49] does not release any dataset, we re-collect the dataset as described in [49]. To accommodate vulnerabilities that do not belong to the datasets [38, 79, 104, 106], we crawl online blogs [4]. Moreover, we accommodate small programs (i.e., smaller than 5K lines of code), which are just as important as large programs but are excluded from the existing datasets mentioned above, by searching vulnerabilities from the NVD spanning between 2010 and 2023. This leads to the identification of seven vulnerabilities with exploits. We remove redundant vulnerabilities according to their CVE IDs, leading to 239 unique vulnerabilities in total.

Step 2: Collecting patches. For the 239 vulnerabilities mentioned above, we collect their patches via their reference links described in the NVD. If a reference link is missing or invalid, the vulnerability is eliminated. In total, we eliminate 61 vulnerabilities, leading to 178 vulnerabilities.

Table 2: Comparison between VUL4C, our benchmark dataset, and existing C/C++ vulnerability datasets

Dataset ¹	#Software	#Vulnerabilities	#CWE types	#Exploits	#Patch	Fidelity	Granularity	VTIIC ²	VTORC ³	Ground truth ⁴	Testability ⁵
SATE IV [88]	–	41,171	116	0	0	Synthesized	Function	0%	0%	0% (0/41,171)	0% (0/41,171)
CVEfixes [6]	563	3,543	133	0	3,574	Real-world	File	0%	0%	0% (0/3,543)	0% (0/3,543)
Big-Vul [31]	348	3,754	91	0	4,432	Real-world	File	0%	0%	0% (0/3,754)	0% (0/3,754)
CrossVul [83]	388	2,167	100	0	2,379	Real-world	File	0%	0%	0% (0/2,167)	0% (0/2,167)
DiverseVul [12]	1,179	2,957	128	0	7,514	Real-world	Function	0%	0%	0% (0/2,957)	0% (0/2,957)
MegaVul [82]	1,062	8,476	176	0	9,288	Real-world	Function	0%	0%	0% (0/8,476)	0% (0/8,476)
ReposVul [122]	601	4,196	151	0	4,699	Real-world	Repository	0%	0%	0% (0/4,196)	0% (0/4,196)
CB-REPAIR [94] ⁶	55	55	36	55	0	Synthesized	Program	100%	0%	0% (0/55)	100% (55/55)
ExtractFix [38]	6	23	9	20	23	Real-world	Program	100%	100%	87% (20/23)	0% (0/23)
VulnLoc [106]	10	36	10	36	36	Real-world	Program	100%	100%	100% (36/36)	0% (0/36)
LinuxFlaw [79]	124	291	17	332	105	Real-world	Program	62.5%	62.5%	34% (100/291)	0% (0/291)
VUL4C	23	144	19	144	144	Real-world	Program	100%	100%	100% (144/144)	47% (68/144)

¹ For vulnerability datasets containing examples of multiples languages, we only report the statistics associated with C/C++ vulnerabilities.

² VTIIC: Vulnerability-Triggering Input Information Coverage, namely the % of vulnerabilities in the dataset that come with information on how to trigger a vulnerability.

³ VTORC: Vulnerability-Triggering Output Results Coverage, namely the % of vulnerabilities in the dataset that come with post-exploitation output information.

⁴ Ground truth is the % of vulnerabilities in the vulnerability dataset with exploit, patch, vulnerability-triggering input information, and vulnerability-triggering output results.

⁵ Testability means the % of vulnerabilities in the vulnerability dataset that come with test cases.

⁶ CB-REPAIR only provides vulnerable programs but not the number of vulnerabilities in each program, forcing us to count #Vulnerabilities and #Exploits as #Software.

Step 3: Testing vulnerability exploitability. Given the 178 vulnerabilities, we (re-)build the vulnerable programs to which they belong. We use the associated exploits to assure that the vulnerabilities can be exploited by leveraging sanitizers to generate error reports on whether an exploitation is successful or not [38, 110, 148]. Examples of sanitizers include AddressSanitizer (ASAN) [99], UBSAN [66], and Low-fat Pointer [26, 27]. If a vulnerability is not successfully exploited, then it is eliminated. This leads to the elimination of 34 vulnerabilities, resulting in a benchmark of 144 vulnerabilities, which correspond to 19 CWE types and 23 software products (cf. Appendix C for details).

Step 4: Collecting test cases. To collect test cases for the 23 software products, we use their built-in test modules, which contain test scripts and test inputs. We execute these test modules to ensure that the associated test cases are valid. In total, we are able to collect test cases for 11 software product, as the other 12 software products do not have any test module in their repository or their test cases fail.

7 Evaluation of AVR Tools

7.1 Experiment Design

Collecting AVR tools. It is known to be difficult to evaluate AVR tools via real-world vulnerabilities [59, 94]. This is reaffirmed with the fact that we are only able to evaluate nine out of the 37 AVR tools collected by this study (cf. Appendix D.1).

For C/C++ programs, we evaluate seven AVR tools recently published in top-tier conferences or journals for repairing vulnerabilities: VRepair [14], VulRepair [34], VQM [33], VulMaster [151], Senx [49], ExtractFix [38], and VulnFix [148]. Among them, Senx [49] is not open-source but we obtain its binary from the authors; VulMaster [151] is open-source but missing the data preprocessing code in the public repository, which we obtain from the authors (but only for C/C++).

For AVR tools geared towards Java programs, we consider two tools, Seader [146] and SeqTrans [18], but not VulMaster [151] because we could not obtain its data preprocessing code from the authors.

Table 3: The number of vulnerabilities for testing AVR tools

Benchmark	Tool	Applicable reasons	# Tests
VUL4C	VulRepair [34]	Only apply to single-file vulnerabilities they can process	81
	VRepair [14]		
	VQM [33]		
	VulMaster [151]		
	VulnFix [148]		
VUL4J	ExtractFix [38]	Only apply to vulnerabilities with their applicable types and compiled on their special compiler	69
	Senx [49]		85
	Seader [146]	Only apply to compilable vulnerabilities	68
	SeqTrans [18]	Only apply to single-line and compilable vulnerabilities	15

Benchmarks. We use VUL4C to evaluate the seven AVR tools and the third-party VUL4J [9] to evaluate the two AVR tools. Table 3 summarizes the number of vulnerabilities that are suitable for evaluating the nine AVR tools. The four learning-based AVR tools [14, 33, 34, 151] evaluated by VUL4C can only repair single-file vulnerabilities, leading to 81 vulnerabilities in each case. VulnFix [148] can only repair vulnerabilities with UBSAN or ASAN sanitizers, leading to 135 vulnerabilities. Both ExtractFix [38] and Senx [49] rely on specific compiler versions and can only repair certain vulnerability types, leading to 69 and 85 vulnerabilities, respectively. For the two AVR tools geared towards Java programs, Seader [146] is evaluated by all the 68 compilable vulnerabilities in VUL4J, while SeqTrans [18] can only fix vulnerabilities requiring single-line modifications (leading to 15 vulnerabilities).

Training for AVR tools. Among the seven AVR tools geared towards C/C++ programs, four [14, 33, 34, 151] belong to learning-based patch generation, meaning that we need to train their models. For this purpose, we use the union of the Big-Vul dataset [31] and the CVEfixes [6] dataset, removing the duplicates between them and the vulnerabilities that are already contained our benchmark VUL4C. We use 80%

of the resulting dataset for training and 20% for validation. Among the two AVR tools [18, 146] geared towards Java programs, one [18] belongs to learning-based patch generation, for which we use the model provided by its authors.

Experiments design. We conduct experiments for three purposes. The first purpose is to evaluate the automated vulnerability analysis step of AVR tools, geared towards C/C++ programs and Java programs alike. For this purpose, we observe that it is difficult to quantify some characteristics (e.g., security properties). Thus, we focus on evaluating the accuracy of fix locations because they point out where a patch should be applied and thus are critical to the subsequent patch generation. We also observe that only two (of the nine) AVR tools provide their own vulnerability analysis [38, 49] and that the non-modular design of Senx [49] makes it impossible to carve out its vulnerability analysis. Thus, we use a localization tool, VulnLoc [106], to identify fix locations. For each vulnerability, we set the maximum execution time as four hours to prevent them from running indefinitely, which is the default time used in [106]. We use following metrics to evaluate the competency of the vulnerability analysis step.

- **File-level accuracy.** Let x denote the number of test vulnerabilities for which an AVR tool correctly localizes the files that need to be fixed and y the total number of test vulnerabilities that are used to evaluate the AVR tool. This metric is defined as $x/y \times 100\%$.
- **Statement-level accuracy.** Let x denote the number of test vulnerabilities for which an AVR tool correctly localizes the fix locations in terms of the lines of code (or statements) that need to be fixed and y the total number of test vulnerabilities that are used to evaluate the AVR tool. This metric is defined as $x/y \times 100\%$.

The second purpose is to evaluate the automated patch generation step of AVR tools via a unified automated patch validation step. For learning-based patch generation methods [14, 18, 33, 34, 151], we set the beam size as 50, meaning that each AVR tool generates 50 candidate patches for each applicable vulnerability. We set their maximum execution time as one hour for each vulnerability, as suggested in [84, 102]. We use following metrics for evaluation.

- **Patch restoration rate.** Let x denote the number of candidate patches that can be successfully applied to their respective test vulnerabilities (i.e., successfully modify the vulnerable code but does not guarantee that the modified code fixed the vulnerability) and y the total number of candidate patches. This metric is defined as $x/y \times 100\%$.
- **Patch compilation rate.** Let x denote the number of candidate patches that can be successfully compiled and y the total number of candidate patches. This metric is defined as $x/y \times 100\%$.
- **Test pass rate.** Let x be the number of candidate patches that successfully pass triggering tests (via exploits) and functions tests (via test cases) and y the total number of candidate patches. It is defined as $x/y \times 100\%$.

The third purpose is to manually evaluate the validity of plausible patches that passed the automated patch validation step of AVR. This is important because a plausible patch that passes automated patch validation still can fail to fix a vulnerability. For this purpose, we compare an plausible patch with the human-crafted patch in question. This allows us to consider semantically equivalent patches. Specifically, we use following metrics.

- **Consistency rate.** Let x denote the number of test vulnerabilities for which an AVR tool generates at least one candidate patch that is the same as the human-crafted ground-truth patch and y the total number of test vulnerabilities. It is defined as $x/y \times 100\%$.
- **Success rate.** Let x denote the number of test vulnerabilities for which an AVR tool generates at least one candidate patch that is the same or semantically equivalent to the human-crafted ground-truth patch and y the total number of test vulnerabilities that are used to evaluate the AVR tool. This metric is defined as $x/y \times 100\%$.

This involvement of domain experts (i.e., co-authors of the present paper) is a common practice in APR and AVR research, as shown in (e.g.) [139, 140, 148]. As elaborated in the ‘‘Ethics Considerations’’ below, there are no ethical concerns, nor IRB is required.

Experimental platform and parameters. Our experiments are conducted on a computer with four 16-core 2.90GHz Intel(R) Xeon(R) Gold 6226R CPUs, 256 GB RAM, and two NVIDIA RTX A6000 GPUs.

7.2 Experimental Results for AVR Tools Geared Towards C/C++ Programs

7.2.1 Evaluating Vulnerability Analysis (Localization)

Table 4 summarizes the vulnerability analysis (localization) results of ExtractFix [38] and VulnLoc [106] where we use the top- k ($k = 1, 3, 5$) locations in the sorted fix locations returned by VulnLoc. We observe that the total number of fix locations returned by ExtractFix is much smaller than 144 (i.e., the number of vulnerabilities in our benchmark dataset). This discrepancy is incurred by the fact that it is only applicable to some vulnerability types or may not produce results at all. Experimental results show that ExtractFix and VulnLoc, both leveraging dynamic analysis techniques to trigger vulnerabilities, achieve a high file-level accuracy (68.4% for ExtractFix and 59.3% for VulnLoc) in localizing fix locations. However, their statement-level accuracy remains low, indicating that these tools can effectively identify the files that require modification for patching purposes, but they struggle to precisely pinpoint the exact statements that need to be fixed.

Nevertheless, ExtractFix exhibits a higher statement-level accuracy (31.6%) than VulnLoc, despite being limited to

Table 4: Evaluation results of the applicable AVR tools’ C/C++ vulnerability localization capabilities

Tool	ExtractFix [38]	VulnLoc [106] (top-1)	VulnLoc [106] (top-3)	VulnLoc [106] (top-5)
File-level accuracy	68.4% (13/19)	41.8% (38/91)	51.6% (47/91)	59.3% (54/91)
Statement-level accuracy	31.6% (6/19)	7.7% (7/91)	13.2% (12/91)	14.3% (13/91)

memory-related vulnerabilities. This relatively high precision can be attributed to ExtractFix’s use of symbolic execution, which incorporates program semantics into its analysis. In contrast, VulnLoc relies on statistical methods and fuzzing-generated test cases, making its results dependent on the quality of the test cases; this explains its low effectiveness. Neither of these two tools provide explanations for the failed analyses (i.e., why they mistakenly identify the claimed fix locations). This lack of explainability hinders failure analysis.

Insight 1 Existing vulnerability analysis methods cannot accurately localize vulnerabilities to statement(s).

7.2.2 Evaluating Patch Generation Capabilities

Table 5 summarizes the number of patches, which are generated by 7 AVR tools and 2 APR tools, that pass the automated patch validation. We observe that the semantics-based patch generator VulnFix [148] outperforms the others with a 96.0% test pass rate, perhaps because its goal is to find a patch invariant to show that an exploit is thwarted. As a result, this approach, and thus VulnFix, generates candidate patches by finding solutions that satisfy the relevant constraints by, for instance, adding conditional checks to prevent a vulnerability from being triggered. Semantics-based patch generation methods [38, 49] outperform learning-based patch generation methods [14, 33, 34, 151] in all three metrics.

Insight 2 AVR tools leveraging semantics-based patch generation methods demonstrate superior effectiveness in generating high-quality patches when compared with the AVR tools leveraging learning-based patch generation methods.

Table 6 summarizes the results with the 7 applicable AVR tools while deferring (i) the detailed results with respect to different vulnerability types, edit types, and each vulnerability in VUL4C, and (ii) an example for explaining semantic equivalence, to Appendix D. Analysis will be provided below.

To understand why the plausible patches fail, we manually analyze them and summarize the reasons in Tables 7 and 8. Specifically, for semantics-based patch generation methods [38, 49, 148], the resulting plausible patches fail due to the following reasons.

First, they fail because of the analysis technique they use. For instance, VulnFix [148], which relies on inferring patch invariants via snapshot fuzzing, fails for the two main reasons: (i) fuzzing-related errors, including missing necessary resources (18 cases) or not being able to generate candidate patch invariants (39 cases) in the course of snapshot fuzzing;

(ii) failure in reducing the candidate patch invariants to a single invariant (20 cases), as shown in the example of Listing D.4.1. Senx [49] fails because of incorrect parsing of pointer variables, as shown in the examples in Appendix D.4.2. ExtractFix [38] fails because of incorrect use of array variables, as shown in the examples in Appendix D.4.3. When applying them to our benchmark, they fail to generate candidate patches or the patched program cannot be compiled successfully, which are the main reason of failure.

Insight 3 The limited effectiveness of semantics-based patch generation tools primarily stems from their limited scalability.

```

@@ -323,8 +350,11 @@ bool copyaudiodata (AFilehandle infile,
    AFilehandle outfile, int trackid)
{
    int frameSize = afGetVirtualFrameSize(infile, trackid,
        1);
-   const int kBufferFrameCount = 65536;
-   void *buffer = malloc(kBufferFrameCount * frameSize);
+   int kBufferFrameCount = 65536;
+   int bufferSize;
+   while (multiplyCheckOverflow(kBufferFrameCount,
        frameSize, &bufferSize))
+       kBufferFrameCount /= 2;
+   void *buffer = malloc(bufferSize);

    AFframecount totalFrames = afGetFrameCount(infile,
        AF_DEFAULT_TRACK);
    AFframecount totalFramesWritten = 0;

```

Listing 1: The manual patch for CVE-2017-6838 (audiofile)

```

@@ -324,6 +324,7 @@
    int frameSize = afGetVirtualFrameSize(infile, trackid,
        1);

    const int kBufferFrameCount = 65536;
+   if (!(frameSize < 32768)) exit(1);
    void *buffer = malloc(kBufferFrameCount * frameSize);

    AFframecount totalFrames = afGetFrameCount(infile,
        AF_DEFAULT_TRACK);

```

Listing 2: The plausible patch generated by VulnFix for CVE-2017-6838 (audiofile)

Second, all these methods suffer from the patch overfitting problem. More specifically, they generate if-condition patches, which render vulnerability-triggering locations unreachable and thus lead to plausible but invalid patches. Still, the plausible but invalid patches may alleviate the repairing

Table 5: Evaluation results of the applicable AVR tools’ patch validation outcomes

Tool	Patch restoration rate	Patch compilation rate	Test pass rate
VulnFix [148]	100.0% (25/25)	100.0% (25/25)	96.0% (24/25)
ExtractFix [38]	100.0% (16/16)	50.0% (8/16)	18.8% (3/16)
Senx [49]	100.0% (19/19)	52.6% (10/19)	15.8% (3/19)
VRepair [14]	31.3% (1269/4050)	2.6% (106/4050)	0.2% (10/4050)
VulRepair [34]	66.5% (2695/4050)	12.5% (507/4050)	4.3% (175/4050)
VQM [33]	69.9% (2829/4050)	11.8% (479/4050)	0.8% (31/4050)
VulMaster [151]	78.9% (3197/4050)	13.9% (564/4050)	1.6% (66/4050)

Table 6: Evaluation results of the applicable AVR tools’ candidate patch generation capabilities for C/C++ vulnerabilities

Tool	Consistency rate	Success rate
VulnFix [148]	5.9% (8/135)	10.4% (14/135)
ExtractFix [38]	1.4% (1/69)	1.4% (1/69)
Senx [49]	0.0% (0/85)	0.0% (0/85)
VRepair [14]	0.0% (0/81)	0.0% (0/81)
VulRepair [34]	0.0% (0/81)	0.0% (0/81)
VQM [33]	0.0% (0/81)	0.0% (0/81)
VulMaster [151]	2.5% (2/81)	2.5% (2/81)

burdens on developers because they can serve as a temporary mitigation to prevent vulnerability exploitation while developers only need to make minor adjustments on this basis to obtain valid patches. To see this, we consider Listings 1 and 2. For CVE-2017-6838, the human-crafted patch checks the size of buffer allocation via function `multiplyCheckOverflow`, then limits the allocation of `buffer` in $65536/2 = 32678$ to make the program run correctly while VulnFix [148] generates a plausible patch. Its conditions are equivalent to the human-crafted patch, but VulnFix chooses to end the program with exit code 1. Thus, a developer can still get the correct conditions from the plausible patches.

Insight 4 *The plausible patches generated by semantics-based patch generation methods can serve as a temporary mitigation to prevent vulnerability exploitation, and developers can obtain valid patches with only minor modifications.*

AVR tools leveraging learning-based patch generation methods [14, 34] exhibit failures at various validation stages (e.g., patch placement and patch compilation, as shown in Table 5). To understand the causes of these patch generation failures, we analyze the 4,050 candidate patches (i.e., 81 vulnerabilities \times 50 candidate patches for each vulnerability) generated in our experiments. Since [14, 33, 34, 151] do not follow the AVR workflow we propose (missing validation process), their original evaluation is based on comparing code sequence equivalence, which is inherent to their data preprocessing pipelines. When placing their generated patches (i.e., code fragments) back into the vulnerable code, issues may arise. This is the main reason for their failure. Note that all the four tools employ the three tokens to mark contexts of the patch designed by VRepair [14]. If the first three tokens are predicted by models incorrectly, the patch can not be placed (i.e, error in generating context tokens). Even with correct

context, mismatches may still cause patch placement failures (i.e., error in matching context) due to the error patch placement strategy designed by VRepair [14]. The model may also introduce other issues, such as generating syntactically incorrect sequences or producing unknown tokens. We show 4 examples accounting for those 4 reasons in Appendix D.4.4 to D.4.7. So the code sequence they generate may not actually fix the vulnerabilities, even though it is the same as the ground truth they process. This incomplete assessment and evaluation framework may stem from the lack of an evaluation benchmark.

Insight 5 *AVR tools leveraging learning-based patch generation methods lack rigorous evaluation methodologies. The processed token sequences fail to accurately reflect their actual repair effectiveness due to the absence of comprehensive benchmarking in the AVR field.*

7.3 Experimental Results for AVR Tools Geared Towards Java Programs

Table 9 summarizes the experimental results. We observe that the two AVR tools for Java programs also perform poorly, which can be understood as follows. First, the poor performance of template-based patch generation methods can be attributed to the diversity of templates and their narrow scope of applicability. Even though Seader [146] performs well in addressing cryptography-related API misuses, it performs poorly when dealing with other types of vulnerabilities. Second, learning-based patch generation methods [18] usually generate syntactically incorrect, and thus useless patches (e.g., presence of undefined macro and variables).

Insight 6 *Current AVR tools for Java are incompetent.*

8 Future Research Directions

Direction 1: Developing effective vulnerability analysis techniques for patch generation. Table 1 shows that many AVR tools lack the support of competent vulnerability analysis. Many learning-based patch generation methods [14, 18, 33, 34, 151] attempt to avoid vulnerability analysis and will inevitably fail; in contrast, semantics-based patch generation methods intend to leverage vulnerability analysis

Table 7: Statistics of causes of failures for *semantics-based* patch generation methods in two steps: patch generation and patch validation, where x is the number of test vulnerabilities that failed and y is the total number of test vulnerabilities. Note that a test vulnerability may fail for reasons, as there can be multiple candidate patches for a vulnerability.

Tool	Patch generation		Patch validation	
	Fail to generate candidate patches	Compilation error	Test failure	Semantic inequivalence
VulnFix [148]	81.48% (110/135)	0.00% (0/135)	0.74% (1/135)	7.41% (10/135)
ExtractFix [38]	82.61% (57/69)	7.25% (5/69)	7.25% (5/69)	1.45% (1/69)
Senx [49]	77.65% (66/85)	10.59% (9/85)	8.23% (7/85)	3.53% (3/85)

Table 8: Statistics of the causes of failures for learning-based patch generation methods

Cause of failures	VulRepair [34]	VRepair [14]	VQM [33]	VulMaster [151]
Error in generating context tokens	81.78% (3312/4050)	91.53% (3707/4050)	75.28%(3049/4050)	62.91%(2548/4050)
Error in matching context	6.12% (248/4050)	0.00% (0/4050)	3.90%(158/4050)	8.49%(344/4050)
Syntax error	8.89% (360/4050)	3.48% (141/4050)	8.05%(326/4050)	13.31%(539/4050)
Unknown tokens	0.00% (0/4050)	1.21% (49/4050)	0.00% (0/4050)	0.00% (0/4050)
Other reasons	3.21% (130/4050)	3.98% (161/4050)	12.77%(517/4050)	15.23%(617/4050)

Table 9: Evaluation of AVR tools for Java programs

Tool	Seader [146]	SeqTrans [18]
Patch restoration rate	100% (8/8)	100% (750/750)
Patch compilation rate	0% (0/8)	0.8% (6/750)
Test pass rate	0% (0/8)	0.1% (1/750)
Consistency rate	0% (0/68)	6.7%(1/15)
Success rate	0% (0/68)	6.7%(1/15)

and often result in high-quality patches (e.g., a higher patch compilation rate and a higher test pass rate as shown in Table 5). Thus, future research should strive to design better automated vulnerability analysis techniques. Notably, some vulnerability detection and analysis methods, such as root cause analysis [91, 133] and learning-based detection [61, 75], have made significant progress in identifying fix locations.

Direction 2: Integrating multiple AVR methods. Since different AVR methods have their own strengths and weaknesses, it is possible to take advantage of their strengths, such as: (i) search-based methods can generate patches with a high test pass rate when guided by objectives (e.g., test pass rate); (ii) template-based patch generation methods can use matching or similarity techniques to deal with simple vulnerabilities, such as integer overflow, buffer overflow, and NULL pointer dereference because they are usually patched via type conversion or if-else checks; (iii) semantics-based patch generation methods are more suitable for memory-related vulnerabilities because they can leverage the constraints that are violated by overflows to generate if-else checks, thereby enhancing memory security; and (iv) learning-based patch generation methods can be applied to uncommon and complex scenarios, thus incorporating templates into learning-based methods [62, 129] might overcome the limited generalization capability of template-based methods while mitigating the weakness of random generation used by learning-based methods.

Direction 3: Leveraging LLMs to improve the effectiveness of AVR. LLMs with extensive parameters, such as GPT-

4, have showed significant value in software security [45], including vulnerability detection [112], penetration testing [23], and fuzzing [73]. There are also empirical studies [64, 93] in AVR that prove their effectiveness in assisting software security. LLMs excel in analyzing vulnerability code, such as identifying critical variables and key code snippets to help understand vulnerabilities, and parsing and interpreting documents to learn secure coding practices to support AVR. LLMs can help generate repair suggestions [144], which can be used as input to learning-based AVR methods. LLMs can interact with external tools in automated analysis and thus vulnerability repair [127]. To enhance LLMs in AVR, it is necessary to build a comprehensive vulnerability knowledge base or knowledge graph, which would include essential information such as vulnerability types, historical repair cases, and developer guidelines. Moreover, LLMs can leverage the *Retrieval-Augmented Generation* (RAG) technology [57] to access and integrate relevant information from the knowledge base and deliver targeted and context-aware solutions.

Direction 4: Balancing security and functionality in search-based, semantics-based, and template-based patch generation methods. Most patch generation methods prioritize rapid treatment of known vulnerabilities, often at the expense of preserving a program’s functionality. Search-based methods try to balance security and functionality via testing, but may lead to functional impairments because test cases can hardly cover all possible scenarios. Semantics-based methods might fix vulnerabilities by adding simple conditional statements, but can cause functionality issues; moreover, developers often prefer nuanced repair strategies, such as refining loop conditions to eliminate vulnerabilities while maintaining a program’s functionality. Template-based methods may suffer from the same problem because predefined templates may lack the flexibility in addressing complex logic, diverse coding styles, or novel attack vectors, resulting in ineffective patches or even new security risks. Furthermore, applying templates often requires significant contextual adjustments to

avoid the disruption of the other parts of a program, adding complexity to the repair process. Future research should emphasize minimizing the impact of repairs on program logic.

Direction 5: Designing effective automated vulnerability validation methods. Designing effective automated vulnerability validation methods is a challenge. Although AVR tools have made progress in generating candidate patches, the lack of a robust and efficient validation mechanism remains a significant limitation. As a result, these tools often produce a large number of candidate patches that overwhelm developers in identifying the competent one. Moreover, unverified patches may introduce new issues or fail to completely resolve a vulnerability, undermining users’ trust in AVR tools [84]. Future research should develop advanced and efficient vulnerability validation methods.

9 Conclusion

We have systematized AVR via its work flow of vulnerability localization, patch generation, and patch validation. To fairly evaluate AVR tools, we propose a benchmark dataset for C/C++ vulnerabilities. We apply the benchmark dataset to empirically evaluate nine AVR tools, leading to important findings, such as: the accuracy of vulnerability localization largely affects repairing effectiveness but existing localization techniques are incompetent; fuzzing-based and symbolic execution-based AVR tools generate compilable patches but may suffer from the patch overfitting problem. We discuss five future research directions.

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Ethics Considerations

We have read the ethics considerations discussions in the conference call for papers, the detailed submission instructions, and the guidelines for ethics documentation.

We thank the anonymous reviewers for their insightful comments. Our experience is that leveraging domain experts to evaluate technical matters does not require IRB approval because human subjects are not the target of studies. This is also shown in prior studies that leverage domain experts to verify the effectiveness of APR or AVR, such as [139, 140, 148].

Nevertheless, we always stick to ethical practice when conducting this and other studies. Inspired by the comments, we now clarify the scope of human involvement in two aspects.

First, in the course of constructing the benchmark, we (i.e., co-authors of this paper) strictly followed the public fuzzing reports to reproduce the experiments associated with the collected vulnerable software and their exploits. Note that for verifying their sanitizer outputs, it is necessary to leverage the reports because semantics-based AVR requires the information provided by the sanitizer for localization purposes.

Second, we (i.e., co-authors) manually evaluate the success rate because automated patch validation cannot guarantee correctness. Moreover, simply comparing plausible patches against the ground-truth patches (crafted by developers) may overlook semantically equivalent patches. Therefore, we also introduce the success rate metric to quantify the degree to which plausible patches are aligned with the ground-truth ones. When semantic equivalence is involved (see Appendix D.2 for examples), it is a common practice to evaluate plausible patches of APR and AVR with human involvement, which is why we (i.e., co-authors) examine manually. Again, this practice does not need IRB approval based on our experience and the literature (see, e.g., [139, 140, 148]).

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We have released our benchmark dataset, experimental code, and results at <https://doi.org/10.5281/zenodo.15609776>.

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Appendix

A Vulnerability Location vs. Fix Location

We use examples to show that fix location may or may not be the same as vulnerability location. For the former, Listing 3 shows a buffer overflow vulnerability (CVE-2024-26889 [2]) caused by the `strcpy` function. The patch is to replace `strcpy` with `strncpy`, showing fix location and vulnerability location are identical.

```
@@ -908,7 +908,7 @@ int hci_get_dev_info(void __user *arg)
     else
         flags = hdev->flags;
-     strcpy(di.name, hdev->name);
+     strncpy(di.name, hdev->name, sizeof(di.name));
     di.bdaddr = hdev->bdaddr;
     di.type = (hdev->bus & 0x0F) | ((hdev->dev_type & 0
         x03) << 4);
     di.flags = flags;
```

Listing 3: An example of CVE-2024-26889 for showing vulnerability fix location is the same as vulnerability location.

```
@@ -394,27 +394,30 @@ void receive_tcp packet(connection_t *c,
     const char *buffer, int len)
void receive_tcp packet(connection_t *c, const char *buffer,
int len) {
    vpn_packet_t outpkt;
+   if(len > sizeof outpkt.data)
+   return;
+
    outpkt.len = len;
    if(c->options & OPTION_TCPONLY)
        outpkt.priority = 0;
    else
        outpkt.priority = -1;
    memcpy(outpkt.data, buffer, len);

    receive_packet(c->node, &outpkt);
}
```

Listing 4: An example of CVE-2013-1428 for showing fix location and vulnerability location are different.

For the latter, Listing 4 shows another buffer overflow vulnerability (CVE-2013-1428 [1]) caused by the `memcpy` function. The patch is to add the colored statements to check the copy length, showing fix location is different from vulnerability location.

B On Adaptability of Abstract Templates

We justify the limited adaptability of abstract templates as follows. First, abstract templates are not applicable to different vulnerability types. Listing 5 presents an abstract template for

fixing cryptographic misuse, where the fix is to replace an insecure hash function with a secure one (i.e., replacing variable `$ssl` in the `insecureset` of hash functions with the one in the `secureset` of hash functions (i.e., SHA-256)). However, this template would not work for other vulnerability types, such as Null Pointer Exception (NPE) because NPE stems from dereferencing null pointers rather than cryptographic misuse.

```

\\ Abstract Template
MessageDigest.getInstance($ssl);
\\ Operation Set for $ssl
insecureset={MD2, MD5, SHA-1};
secureset={SHA-256};

```

Listing 5: An abstract template used by Seader [146]

Second, abstract templates are, in general, not applicable even to the same type of vulnerabilities. Listing 6 presents an abstract template for fixing the NULL Pointer Dereference (NPD) vulnerability by adding a NULL check, where `obj` should be replaced with the variable causing NPD. Listing 7 presents a developer-crafted patch to CVE-2017-13710 (NPD vulnerability), where the fix includes a resource release operation (Line 16). When applying this abstract template to fix CVE-2017-13710, the fix only adds a `return` statement under the `if`-condition, causing the missing resource release operation to execute prior to the execution of the `return` statement and thus a failure in fixing the vulnerability.

```

\\ Add NULL pointer check to avoid NPD
+ if (obj == null){
+   return ;
+ }

```

Listing 6: An abstract template used by VFix [134]

C Vulnerability Types and Software Products Involved in VUL4C

Table 10 lists the 19 vulnerability types contained in VUL4C. As mentioned above, it contains 144 vulnerabilities. The top-5 vulnerability types are: 35 Buffer Overflow vulnerabilities (CWE-119), 29 Out-of-bounds Read vulnerabilities (CWE-125), 16 NULL Pointer Dereference vulnerabilities (CWE-476), 14 Out-of-bounds Write vulnerabilities (CWE-787), and 11 Divide By Zero vulnerabilities (CWE-369).

Table 11 lists all the 23 software products and their corresponding repository links, where “✓” denotes that a test case runs successfully and “✗” otherwise. Among the 23 products, 12 are client software, nine are libraries, and two are utilities. Moreover, the `libtiff` library contains the most vulnerabilities (i.e., 24), followed by the `binutils` utility software (18) and the `jasper` client software (17).

```

1 @@ -742,12 +742,22 @@ setup_group (bfd *abfd,
2     Elf_Internal_Shdr *hdr, asection *newsect)
3     {
4         Elf_Internal_Shdr *shdr = elf_tdata (abfd)->
5             group_sect_ptr[i];
6         Elf_Internal_Group *idx;
7         unsigned int n_elt;
8         bfd_size_type n_elt;
9         if (shdr == NULL)
10            continue;
11            idx = (Elf_Internal_Group *) shdr->contents;
12            if (idx == NULL || shdr->sh_size < 4)
13            {
14                /* See PR 21957 for a reproducer. */
15                /* xgettext:c-format */
16                _bfd_error_handler (_("%B: group section '%A' has no
17                    contents"),
18                    abfd, shdr->bfd_section);
19                elf_tdata (abfd)->group_sect_ptr[i] = NULL;
20                bfd_set_error (bfd_error_bad_value);
21                return FALSE;
22            }
23            n_elt = shdr->sh_size / 4;
24            /* Look through this group's sections to see if current

```

Listing 7: A patch for CVE-2017-13710

Table 10: The 19 vulnerability types contained in VUL4C.

CWE	Description	#CVE
CWE-119	Buffer Overflow	35
CWE-120	Buffer Copy without Checking Size of Input	1
CWE-125	Out-of-bounds Read	29
CWE-189	Numeric Errors	2
CWE-190	Integer Overflow or Wraparound	9
CWE-191	Integer Underflow	1
CWE-20	Improper Input Validation	6
CWE-369	Divide By Zero	11
CWE-415	Double Free	1
CWE-416	Use After Free	4
CWE-476	NULL Pointer Dereference	16
CWE-617	Reachable Assertion	2
CWE-682	Incorrect Calculation	1
CWE-704	Incorrect Type Conversion or Cast	1
CWE-770	Allocation of Resources Without Limits or Throttling	1
CWE-787	Out-of-bounds Write	14
CWE-835	Loop with Unreachable Exit Condition	4
CWE-843	Access of Resource Using Incompatible Type	1
NVD-CWE-Other ¹	Vulnerability Types Not Covered in NVD	5

¹ Note that NVD-CWE-Other is an entry in the NVD CWE Slice Categories [87], meaning that this vulnerability type is not covered in the NVD database.

D More Results on AVR Tools

D.1 Justification on the Nine AVR Tools

As discussed in Section 7.1, we evaluate nine AVR tools, including eight open-source tools and one closed-source tool (i.e., `Senx` [49], for which we obtain its binary from the authors). Among them, seven (including six open-source tools and the closed-source `Senx` [49]) are for C/C++ programs and two for Java programs. In what follows we discuss why the other $37 - 8 = 29$ open-source AVR tools are not evaluated.

- **Language incompatibility.** There are 10 AVR tools that are geared towards Solidity [19, 32, 81, 96, 108, 114, 120], JavaScript [100] or other programming languages [65, 142] than C/C++ and Java, meaning that these 10 cannot be

Table 11: The 23 software products with vulnerabilities contained in VUL4C

Type	Software	Repository Links	#CVE	Test Suites
Utilities	binutils	https://sourceware.org/git/binutils-gdb	18	✗
	elfutils	https://sourceware.org/pub/elfutils	5	✓
Clients	audiofile	https://github.com/mpruett/audiofile	12	✓
	bento4	https://github.com/axiomatic-systems/Bento4	6	✗
	gilcc	https://github.com/trgil/gilcc	1	✗
	graphicsmagick	http://hg.code.sf.net/p/graphicsmagick/code/	3	✓
	imagemagick	https://github.com/ImageMagick/ImageMagick	4	✗
	imageworsener	https://github.com/jsummers/imageworsener	8	✓
	jasper	https://github.com/jasper-software/jasper	17	✗
	jhead	https://github.com/Matthias-Wandel/jhead	2	✗
	ngiflib	https://github.com/miniupnp/ngiflib	4	✓
	openjpeg	https://github.com/uclouvain/openjpeg	5	✗
	qpdf	https://github.com/qpdf/qpdf	3	✓
	zziplib	https://github.com/gdraheim/zziplib	3	✗
	Libraries	libarchive	https://github.com/libarchive/libarchive	3
libcroco		https://gitlab.gnome.org/Archive/libcroco	1	✗
libdwarf		https://github.com/davea42/libdwarf-code	3	✗
libjpeg		https://github.com/libjpeg-turbo/libjpeg-turbo	4	✗
libming		https://github.com/libming/libming	9	✗
libsndfile		https://github.com/libsndfile/libsndfile	3	✓
libtiff		https://github.com/vadz/libtiff	24	✓
libxml2		https://gitlab.gnome.org/GNOME/libxml2	4	✓
	libzip	https://github.com/nih-at/libzip	2	✓

evaluated with VUL4C or VUL4J.

- **Binary code.** One tool [25] is geared towards binary code rather than source code, meaning it cannot be evaluated with VUL4C or VUL4J.
- **Vulnerability type.** Two AVR tools [28, 56] geared towards the NPE vulnerabilities in Java. However, VUL4J does not contain any NPE vulnerability, meaning NPEFix [28] and NPEX [56] cannot be evaluated with VUL4J.
- **Insufficient documentation.** There are 11 AVR tools [16, 17, 35, 44, 54, 55, 72, 102, 103, 113, 118] that lack sufficient documentation or instruction, making it infeasible for us to repeat their experiments. Specifically, [17, 35, 54, 72, 113] only present evaluation results on simple code snippets (e.g., arithmetic operations) rather than programs; MemFix [55] does not offer any guidance on how to use it; CPR [102] requires experts-crafted program constraints without providing instructions on how to do it; FootPatch [118] only provides documentation on building, but not running; SAVER [44] requires detailed information about memory objects, which are not available to us; CrashRepair [103] does not provide instructions on how to write the configuration file when testing new vulnerabilities; the results of IntPTI [16] cannot be replicated by us.
- **Limited scenarios.** There are four AVR tools [90, 101, 104, 139] that are geared towards vulnerability patch transplantation, meaning that they aim to fix the same vulnerability in

different software or different versions by adapting a given patch to different scenarios.

- **Other reasons.** There is one AVR tool, Fix2Fit [37], which may generate thousands of candidate patches from a given exploit owing to the use of fuzzing. Since it does not provide any method to prioritize the candidate patches, it is infeasible to evaluate this large number of candidate patches.

D.2 On Semantic Equivalence of Patches

If a plausible patch is semantically equivalent to a human-crafted ground-truth patch, the plausible patch would not introduce any functionality errors or additional vulnerabilities in the patched program. We give an example in Listings 8 and 9 to explain this.

Listing 8 presents a human-crafted ground-truth patch to CVE-2017-9043 (binutils). The basic idea is to add an if-statement as follows: If the value of `bytes` is greater than `sizeof(val)`, then an error will occur when running the program. Note that the type of `val` is `unsigned long long` after patching, meaning that the value of `sizeof(val)` is 8.

Listing 9 presents a plausible patch generated by VulnFix [148] for CVE-2017-9043. It is semantically equivalent to the human-crafted ground-truth patch presented in Listing 8 because it contains the if-statement `if (!(bytes<=8))` such that an error will occur when the condition is met.

```

@@ -16948,10 +16948,18 @@ print_gnu_build_attribute_name (
    Elf_Internal_Note * pnote)
    {
    case GNU_BUILD_ATTRIBUTE_TYPE_NUMERIC:
    {
-   unsigned int bytes = pnote->namesz - (name - pnote->
      namedata);
-   unsigned long val = 0;
-   unsigned int shift = 0;
-   char * decoded = NULL;
+   unsigned int bytes = pnote->namesz - (name - pnote->
      namedata);
+   unsigned long long val = 0;
+   unsigned int shift = 0;
+   char * decoded = NULL;
+
+   /* PR 21378 */
+   if (bytes > sizeof (val))
+   {
+     error (_("corrupt name field: namesz of %lu is too
      large for a numeric value\n"),
+           pnote->namesz);
+     return FALSE;
+   }

    while (bytes --)
    {

```

Listing 8: A human-crafted ground-truth patch to CVE-2017-9043 (binutils)

```

@@ -16933,6 +16933,7 @@
    unsigned long val = 0;
    unsigned int shift = 0;
    char * decoded = NULL;
+   if (!(bytes <= 8)) exit(1);

    while (bytes --)
    {

```

Listing 9: A semantically equivalent patch generated by VulnFix [148] for CVE-2017-9043 (binutils)

D.3 Further Evaluation Results on AVR Tools

Table 12 summarizes the *success rate* of the nine AVR tools over the top-10 vulnerability types in VUL4C (i.e., the types with the largest number of vulnerabilities). We observe that the AVR tools that target specific vulnerability types are not as effective as the general AVR tools (which are not designed towards specific vulnerability types). For instance, ExtractFix [38] and Senx [49] are designed to address certain vulnerability types (e.g., memory-related vulnerabilities for ExtractFix; bad cast, buffer overflow and integer overflow vulnerabilities for Senx) and achieve a lower success rate than VulnFix [148] which is not geared towards specific vulnerability types. This phenomenon can be understood as follows: ExtractFix and Senx typically address memory-related vulnerabilities by simply adding if-return statements to prevent vulnerabilities from being triggered; whereas, VulnFix uses snapshot fuzzing and considers program states with respect to both positive and negative test cases to generate more precise

condition ranges.

D.4 Case Study of Patch Generation

We provide case studies for the causes of failures. Cases D.4.1 to D.4.3 account for the 3 main causes of failures of semantics-based patch generation methods, and D.4.4 to D.4.7 discuss those of learning-based patch generation methods.

D.4.1 Case Study: CVE-2017-15021 (binutils)

VulnFix [148] generates candidate patch invariants via snapshot fuzzing, reduces them to a single invariant, and synthesizes it into a candidate patch. However, it may fail to reduce candidate patch invariants to a single one within limited fuzzing time, causing a failure. Take vulnerability CVE-2017-15021 in binutils as an example. It fails to produce a single invariant when reaching the time limit (see Listing 10).

```

FAIL (More than one or no patch invariants in the end)

Patch Invariants:
2
['_GSize_name - crc_offset >= 4', '_GSize_contents -
  crc_offset >= 4']

```

Listing 10: The output generated by Vulnfix [148] for CVE-2017-15021 (binutils)

D.4.2 Case Study: CVE-2016-9387 (jasper)

Senx [49] fails when incorrectly parses pointer variables. Take CVE-2016-9387 in jasper as an example, Senx fails to generate `dec->numhtiles` and `dec->numvtiles` but instead generating `dec@numhtiles` and `dec@numvtiles` (see Listing 11).

```

@@ -1231,7 +1232,10 @@ static int jpc_dec_process_siz(
    jpc_dec_t *dec, jpc_ms_t *ms)

    dec->numhtiles = JPC_CEILDIV(dec->xend - dec->tilexoff,
      dec->tilewidth);
    dec->numvtiles = JPC_CEILDIV(dec->yend - dec->tileyoff,
      dec->tileheight);
+   if ((dec@numhtiles)*(dec@numvtiles) > 2147483647)
    dec->numtiles = dec->numhtiles * dec->numvtiles;
    JAS_DBGLOG(10, ("numtiles = %d; numtiles = %d;
      numvtiles = %d;\n",
      dec->numtiles, dec->numhtiles, dec->numvtiles));
    if (!(dec->tiles = jas_alloc2(dec->numtiles, sizeof(
      jpc_dec_tile_t)))) {

```

Listing 11: The candidate patch generated by Senx [49] for CVE-2016-9387 (jasper)

Table 12: Success rate of the seven AVR tools and two APR tools via the top-10 CWE types in VUL4C, where “-” means the tool is not applicable to the CWE.

CWE	AVR							APR	
	VulRepair [34]	VRepair [14]	VQM [33]	VulMaster [151]	VulnFix [148]	ExtractFix [38]	Senx [49]	CquenceR [94]	NTR [48]
CWE-119	0.0%(0/21)	0.0%(0/21)	0.0%(0/21)	4.8%(1/21)	14.3%(5/35)	5.9%(1/17)	0.0%(0/35)	0.0%(0/17)	35.3%(6/17)
CWE-125	0.0%(0/13)	0.0%(0/13)	0.0%(0/13)	0.0%(0/13)	3.4%(1/29)	0.0%(0/13)	0.0%(0/24)	0.0%(0/7)	0.0%(0/7)
CWE-476	0.0%(0/10)	0.0%(0/10)	0.0%(0/10)	0.0%(0/10)	12.5%(2/16)	0.0%(0/7)	-	0.0%(0/5)	0.0%(0/5)
CWE-787	0.0%(0/8)	0.0%(0/8)	0.0%(0/8)	0.0%(0/8)	7.1%(1/14)	0.0%(0/10)	0.0%(0/14)	0.0%(0/5)	0.0%(0/5)
CWE-369	0.0%(0/7)	0.0%(0/7)	0.0%(0/7)	0.0%(0/7)	36.4%(4/11)	0.0%(0/7)	-	0.0%(0/9)	0.0%(0/9)
CWE-190	0.0%(0/6)	0.0%(0/6)	0.0%(0/6)	0.0%(0/6)	0.0%(0/8)	0.0%(0/5)	0.0%(0/9)	-	-
CWE-20	0.0%(0/2)	0.0%(0/2)	0.0%(0/2)	0.0%(0/2)	25.0%(1/4)	-	-	0.0%(0/1)	0.0%(0/1)
CWE-416	0.0%(0/3)	0.0%(0/3)	0.0%(0/3)	0.0%(0/3)	0.0%(0/4)	-	-	-	-
CWE-835	0.0%(0/1)	0.0%(0/1)	0.0%(0/1)	0.0%(0/1)	0.0%(0/4)	-	-	0.0%(0/1)	0.0%(0/1)
CWE-189	0.0%(0/2)	0.0%(0/2)	0.0%(0/2)	0.0%(0/2)	0.0%(0/2)	0.0%(0/1)	-	100.0%(1/1)	100.0%(1/1)

D.4.3 Case Study: CVE-2017-7598 (libtiff)

ExtractFix [38] may fail due to incorrect using of array variables. Take vulnerability CVE-2017-7598 in libtiff as an example, ExtractFix fails to generate `m.i[1]` as it generates `m[1]` (see Listing 12).

```

if (m.i[0]==0)
    *value=0.0;
else
+   if (m[1] != 0) return (TIFFReadDirEntryErrOk);
    *value=(double)m.i[0]/(double)m.i[1];

```

Listing 12: The candidate patch generated by ExtractFix [38] for CVE-2017-7598 (libtiff)

D.4.4 Case Study: CVE-2020-26208 (jhead)

This case illustrates failure reason “Error in generating context tokens” for learning-based methods [14, 33, 34, 151], which rely on the first three context tokens to pinpoint where the candidate patches should make modifications (i.e., generating incorrect context tokens will render the candidate patches incorrect). Take vulnerability CVE-2020-26208 in jhead as an example. The first three tokens “malloc”, “(”, and “itemlen” in the processed target output (see Listing 13), aim to identify the fix location. However, the output generated by VRepair (via these three tokens) [34] is different from the target output (see Listing 14), leading to incorrect candidate patch.

```

<S2SV_ModStart> malloc ( itemlen + 20

```

Listing 13: The target output for CVE-2020-26208 (jhead)

D.4.5 Case Study: CVE-2017-15023 (binutils)

This case is used to illustrate failure reason “Error in matching context” for learning-based methods. Even when the context

```

<S2SV_ModStart> ); } if ( <unk> == NULL ) return FALSE ;

```

Listing 14: The candidate patch generated by VRepair [34] for CVE-2020-26208 (jhead)

tokens generated by the learning-based patch generation methods [14, 33, 34, 151] are consistent with the target, there is no guarantee that the fix location pinpointed by the candidate patch is correct. This is because these methods utilize the first matching context as the fix location to apply the candidate patch. Take the vulnerability CVE-2017-15023 in binutils for example. In the fixed function, there are three lines that are partially consistent with the context “+= bytes_read ;” (see Listing 15). The manual patches are applied to the third of them, while the output generated by the learning-based methods [14, 34] is applied to the first one.

```

for (formati = 0; formati < format_count; formati++)
{
    _bfd_safe_read_leb128 (abfd, buf, &bytes_read, FALSE,
        buf_end);
+   buf += bytes_read ; // Incorrect Location
    _bfd_safe_read_leb128 (abfd, buf, &bytes_read, FALSE,
        buf_end);
+   buf += bytes_read ; // Incorrect Location
}

data_count = _bfd_safe_read_leb128 (abfd, buf, &bytes_read,
    FALSE, buf_end);
+   buf += bytes_read ; // Correct Location
+   if (format_count == 0 && data_count != 0)
+   {
+       _bfd_error_handler (_("Dwarf Error: Zero format count."))
+       );
+       bfd_set_error (bfd_error_bad_value);
+       return FALSE;
+   }
+
for (datai = 0; datai < data_count; datai++)
{
    bfd_byte *format = format_header_data;

```

Listing 15: The manual patch for CVE-2017-15023 (binutils)

D.4.6 Case Study: CVE-2016-9827 (libming)

This case explains the “*Syntax error*” failure for learning-based methods [14, 34], which generate unmatched symbols (e.g., ‘`’` and ‘`)`’) and make compilation fail. Considering vulnerability CVE-2016-9827 in libming (cf. Listing 16), the absence of ‘`’`’ in statement “`TEMP_FAILURE_RETRY(readBytes(f, length));`” makes the patch generated by VulRepair [34] fail to compile.

```
@@ -2752,7 +2752,7 @@ parseSWF_PROTECT (FILE * f, int length)
PAR_BEGIN (SWF_PROTECT);

if (length != 0) {
- parserrec->Password = readBytes (f, length);
+ parserrec -> Password =
  TEMP_FAILURE_RETRY ( readBytes ( f , length ) ;
} else {
  parserrec->Password = NULL;
}
```

Listing 16: The candidate patch generated by VulRepair [34] for CVE-2016-9827 (libming)

D.4.7 Case Study: CVE-2016-9828 (libming)

This case is used to illustrate failure reason “*Unknown tokens*” for learning-based methods. The learning-based patch generation methods [14, 33, 34, 151] may generate unknown tokens, which can lead to the failure of compilation. Take the vulnerability CVE-2016-9828 in libming for example. Due to the undefined token `<unk>` (see Listing 17), the candidate patch generated by VulRepair [34] cannot be compiled.

```
<S2SV_ModStart> ; } }
if ( stream -> blockName [ blockName ] == <unk> ) { return ; }
```

Listing 17: The candidate patch generated by VRepair [34] for CVE-2016-9828 (libming)

E Evaluation of APR Tools

This section reports a side-product on evaluating four open-source APR tools, including two tools for C/C++ programs, namely NTR [48] and CquenceR [94], via our benchmark VUL4C dataset (Appendix E.1); and two APR tools for Java programs, namely ThinkRepair [140] and SRepair [131], via the third-party VUL4J dataset (Appendix E.2). The experimental platform is the same as the one used for evaluating AVR tools. We use the following metrics (defined in Section 7.1) to evaluate these four APR tools, namely: *consistency rate*, *success rate*, *patch restoration rate*, *patch compilation rate*, and *test pass rate*.

E.1 Evaluating APR Tools for C/C++

APR tools and parameters. The configurations of the two APR tools for C/C++ programs are as follows.

- **NTR** [48]. NTR predicts fix templates by fine-tuning CodeT5 [123]. We use the VulGen [85] dataset provided by the authors of [48] to fine-tune NTR and conduct experiments with the single-hunk vulnerabilities in VUL4C. By using the same parameters as in [48], NTR generates 10 candidate patches for each predicted template. We use the Top 5 templates ranked by NTR to generate 50 candidate patches in total.
- **CquenceR** [94]. CquenceR is a C/C++ implementation of SequenceR [15], which is based on the NMT architecture and uses a sequence-to-sequence model to generate patches. In our experiments, we set the beam size to 50 to generate 50 candidates, as in [94]. Note we are only able to evaluate it with the single-hunk vulnerabilities in VUL4C because CquenceR is only applicable to fixes to single-hunk vulnerabilities.

Experimental Results. Table 13 summarizes the results with the two APR tools for C/C++ programs, namely CquenceR [94] and NTR [48]. We make two observations. First, NTR achieves a patch compilation rate and a test pass rate of 71.5% and 8.2%, respectively, which are respectively 43.4% and 4% higher than those of CquenceR (28.1% and 4.2%). This discrepancy can be attributed to the following: CquenceR uses CodeT5 to generate candidate patches at the statement level, resulting in the lack of sufficient contextual information; whereas, NTR employs StarCoder to generate candidate patches at the function level, resulting in the accommodation of more context information. Second, NTR also outperforms CquenceR in terms of consistency rate and success rate. Specifically, NTR achieves a consistency rate of 11.8% and a success rate of 15.7%, while CquenceR only scores 1.9% in both metrics. This can be attributed to the fact that StarCoder has a higher comprehension capability than CodeT5 while leveraging the template-based constraints predicted by CodeT5 to mitigate uncertainty in its code generation; whereas, CquenceR uses the candidate patches generated by CodeT5, but these patches are often different from human-crafted patches.

Insight 7 *APR models with a stronger code comprehension capability perform better; leveraging multiple models can perform even better.*

E.2 Evaluating APR Tools for Java Programs

APR tools and parameters. The configurations of the two APR tools for Java programs are as follows.

- **ThinkRepair** [140]. ThinkRepair is an LLM-based APR tool. It first collects pre-fixed knowledge by *Chain-of-Thought* (CoT) and then fixes bugs via CoT and few-shot

Table 13: Evaluation results of APR tools for generating vulnerability patches

Tool	C/C++		Java	
	CquenceR [146]	NTR [18]	ThinkRepair [140]	SRepair [131]
Patch restoration rate	100.0% (2600/2600)	100.0% (2550/2550)	100% (1619/1619)	100% (2963/2963)
Patch compilation rate	28.1% (731/2600)	71.5% (1822/2550)	53.1% (859/1619)	62.6% (1855/2963)
Test pass rate	4.2% (110/2600)	8.2% (208/2550)	4.9%(79/1619)	9.2% (273/2963)
Consistency rate	1.9% (1/52)	11.8% (6/51)	6.1%(2/33)	6.3% (4/63)
Success rate	1.9% (1/52)	15.7% (8/51)	18.2% (6/33)	14.3% (9/63)

learning. We use the same parameters as in [140], and consider the first 50 resulting candidate patches. Note that patch generation may terminate prematurely when the prompt exceeds 4,096 tokens in the feedback iteration round, leading to less than 50 candidates. Since ThinkRepair is only applicable to single-function vulnerabilities (i.e., a vulnerability resides in a single program function), we select 33 vulnerabilities from the VUL4J dataset after removing the non-compilable projects.

- **SRepair [131]**. SRepair is a CoT-based function-level APR tool. It uses repair suggestion to guide patch generation and demonstrates a higher performance than the closed-source tool ChatRepair [130], while applicable to multi-function vulnerabilities (i.e., vulnerabilities cutting across multiple program functions). Thus, we test it for 63 vulnerabilities from the VUL4J dataset after removing the non-compilable projects. Since GPT-3.5-turbo does not guarantee a sufficient number of repair suggestions, some vulnerabilities may yield fewer than 50 candidate patches.

Experimental Results. Table 13 also summarizes the experimental results for these two tools. We make two observations. First, SRepair achieves a higher patch compilation rate and a higher test pass rate than ThinkRepair. Specifically, SRepair achieves a patch compilation rate of 62.6% and a test pass rate of 9.2%; whereas, ThinkRepair achieves 53.1% and 4.9%, respectively. This discrepancy can be attributed to their CoT strategy: ThinkRepair directly incorporates test messages into prompt templates for patch generation; whereas, SRepair constructs a more sophisticated chain-of-thought process by first guiding LLM to comprehend the test message and generate a repair suggestion, and then using the suggestion to construct an informed prompt for patch generation. Second, SRepair achieves a success rate of 14.3%, which is 3.9% lower than ThinkRepair’s (18.2%). This discrepancy can be attributed to the following: ThinkRepair only handles single-function vulnerabilities, while SRepair deals with more complex cross-function vulnerabilities. More specifically, their CoT only accommodate names of failed test cases and exceptions in VUL4J, namely lacking the vulnerability information (e.g., vulnerability types and locations) that cannot always be inferred by LLMs. This makes APRs often select incorrect fix locations and misidentify vulnerability types.

Insight 8 *Employing detailed thought processes in the CoT framework can enhance LLMs’ patch generation capabilities,*

while lacking vulnerability information leads to repair failures.

E.3 Further Evaluation Results on APR Tools

Table 12 summarizes the *success rate* of the two APR tools over the top-10 vulnerability types in VUL4C (i.e., the types with the largest number of vulnerabilities). We observe that NTR’s success rate on CWE-119 is significantly higher than that of CquenceR on CWE-119. This suggests that directly generating patches through training-based methods has a high error rate, and that using a deep learning model for simple template prediction yields a higher success rate. We also observe that NTR’s success rate remains very low for the other vulnerability types (than CWE-119), suggesting that LLMs have varying capabilities in repairing different types of vulnerabilities. Nevertheless, LLMs can identify and fix memory buffer vulnerabilities.

F Detailed Results for AVR and APR

Table 14 summarizes the detailed evaluation results on the patch generation capabilities of the seven AVR tools and the two APR tools via VUL4C. We show evaluation results which at least one AVR tool or APR tool generates valid candidate patches (i.e., can be successfully applied to vulnerabilities). Table 15 summarizes the detailed evaluation results on the patch generation capabilities of the two AVR tools and two APR tools via VUL4J, where the results can be understood as follows: for the notation $a/b/c/d$, a denotes the total number of valid candidate patches, b denotes the total number of compilable patches, c denotes the total number of patches that pass the test, d denotes the number of correct patches; CE denotes that an AVR tool encounters a compilation error when testing a vulnerability; TO denotes that an AVR tool times out when testing a vulnerability; - denotes that an AVR tool is not applicable to a vulnerability; ✗ denotes that an AVR tool fails to generate a patch for a vulnerability; AE denotes an assertion error defined by developer.

Table 14: comparing patch generation capabilities of the seven AVR tools and two APR tools with respect to VUL4C

Software	Vulnerable program			AVR							APR		
	CVE ID	CWE	Sanitizer	VRRepair [14]	ValRepair [34]	VQM [33]	VulMaster [151]	VulnFix [148]	ExtractFix [38]	Senx [49]	CqenceR [94]	NTR [48]	
audiofile	CVE-2017-6828	CWE-119	ASAN	--	--	--	--	X	CE	X	50/15/4/0	50/46/10/1	
	CVE-2017-6827	CWE-119	ASAN	--	--	--	--	X	CE	X	50/16/4/0	50/46/5/1	
	CVE-2017-6832	CWE-119	ASAN	--	--	--	--	X	CE	X	50/15/0/0	50/46/2/0	
	CVE-2017-6833	CWE-369	ASAN	--	--	--	--	X	CE	--	50/18/0/0	50/46/0/0	
	CVE-2017-6835	CWE-369	ASAN	--	--	--	--	X	CE	--	50/18/0/0	50/46/0/0	
bento4	CVE-2017-6838	CWE-190	UBSAN	X	47/44/0	44/0/0/0	50/0/0/0	1/1/1/0	CE	X	--	--	
	CVE-2017-14640	CWE-476	ASAN	--	--	--	--	X	CE	--	50/15/8/0	50/19/0/0	
	CVE-2017-14729	CWE-119	ASAN	7/0/0/0	4/0/0/0	43/0/0/0	50/2/0/0	X	CE	1/1/0/0	50/10/0/0	50/47/0/0	
	CVE-2017-14745	CWE-190	ASAN	--	--	--	--	X	CE	X	--	--	
	CVE-2017-14959	CWE-125	ASAN	34/0/0/0	6/0/0/0	50/0/0/0	--	X	CE	X	--	--	
binutils	CVE-2017-14940	CWE-476	ASAN	47/0/0/0	50/0/0/0	43/0/0/0	1/0/0/0	50/0/0/0	X	CE	--	50/11/0/0	
	CVE-2017-15020	CWE-125	ASAN	11/7/0/0	40/0/0/0	49/1/0/0/0	50/2/0/0/0	X	CE	X	--	50/37/0/0	
	CVE-2017-15021	CWE-125	ASAN	X	49/3/0/0	48/3/0/0	50/5/0/0	X	CE	X	50/13/0/0	50/49/0/0	
	CVE-2017-15022	CWE-476	ASAN	40/0/0/0	50/0/0/0	X	50/0/0/0	TO	CE	--	--	--	
	CVE-2017-15023	CWE-476	ASAN	1/1/0/0	50/30/30/0	46/0/0/0	50/0/0/0	X	CE	--	50/7/1/0	50/39/18/0	
	CVE-2017-15024	CWE-835	ASAN	X	X	X	50/0/0/0	X	CE	--	--	--	
	CVE-2017-15025	CWE-369	ASAN	7/0/0/0	19/14/0/0	50/0/0/0	50/13/0/0	1/1/1/1	CE	--	50/3/1/0	50/50/6/0	
	CVE-2017-15958	CWE-119	ASAN	15/0/0/0	50/1/0/0	50/0/0/0	48/1/0/0	X	CE	X	--	--	
	CVE-2017-15939	CWE-119	ASAN	4/1/0/0	49/24/0/0	50/0/0/0	50/0/0/0	1/1/1/1	CE	X	--	--	
	CVE-2017-6965	CWE-119	ASAN	X	X	X	X	X	CE	X	--	--	
	CVE-2017-9038	CWE-125	ASAN	33/0/0/0	1/1/0/0	X	38/0/0/0	X	CE	X	50/0/0/0	50/0/0/0	
	CVE-2017-9040	CWE-476	ASAN	9/0/0/0	45/0/0/0	1/0/0/0	50/0/0/0	X	CE	--	--	--	
	CVE-2017-9042	CWE-704	UBSAN	10/0/0/0	43/0/0/0	1/0/0/0	50/0/0/0	X	CE	X	--	--	
	CVE-2017-9043	CWE-20	UBSAN	X	8/0/0/0	50/0/0/0	50/1/0/0	1/1/1/1	CE	--	--	--	
	elfutils	CVE-2018-10372	CWE-125	ASAN	17/0/0/0	X	50/0/0/0	23/0/0/0	X	CE	X	50/15/0/0	50/0/0/0
CVE-2017-7607		CWE-125	ASAN	50/0/0/0	50/18/0/0	50/0/0/0	43/22/20/0	X	CE	50/40/0/0	50/50/0/0		
CVE-2017-7610		CWE-125	ASAN	X	4/0/0/0	43/0/0/0	X	X	CE	CE	--	--	
CVE-2017-7611		CWE-125	ASAN	X	X	21/0/0/0	X	X	CE	CE	50/13/0/0	50/46/0/0	
CVE-2017-7612		CWE-125	ASAN	X	50/0/0/0	33/0/0/0	3/0/0/0	X	CE	CE	--	--	
graphicsmagick	CVE-2017-12937	CWE-125	ASAN	27/0/0/0	X	X	X	1/1/0/0	X	1/1/0/0	--	--	
imagemagick	CVE-2016-9556	CWE-119	ASAN	50/10/8/0	50/42/42/0	15/6/6/0	6/0/0/0	1/1/1/0	CE	1/1/1/0	50/11/0/0	50/45/0/0	
	CVE-2017-12876	CWE-787	ASAN	--	--	--	--	1/1/1/0	CE	1/1/1/0	--	--	
imagemagick	CVE-2017-12877	CWE-416	ASAN	24/0/0/0	50/0/0/0	9/0/0/0	50/0/0/0	X	CE	--	--	--	
	CVE-2017-7962	CWE-369	ASAN	4/0/0/0	50/3/0/0	40/0/0/0	50/19/17/0	X	CE	--	50/9/4/0	50/46/0/0	
	CVE-2017-8325	CWE-119	ASAN	--	--	--	--	TO	X	1/1/0/0	50/0/0/0	--	
	CVE-2017-9206	CWE-125	ASAN	--	--	--	--	1/1/0/0	X	X	--	--	
	CVE-2016-10248	CWE-476	ASAN	X	50/2/2/0/0	33/0/0/0	354/0/0/0	X	CE	X	50/8/0/0	50/32/0/0	
jasper	CVE-2016-10251	CWE-190	ASAN	27/0/0/0	46/1/0/0	40/0/0/0	48/0/0/0	X	1/0/0/0	X	--	--	
	CVE-2016-8691	CWE-369	ASAN	X	49/40/0/0	50/2/1/0/0	50/28/0/0	1/1/1/0	X	--	50/13/0/0	50/42/0/0	
	CVE-2016-8692	CWE-369	ASAN	X	49/40/0/0	50/22/0/0	50/27/0/0	X	X	--	50/11/0/0	50/42/0/0	
	CVE-2016-8884	CWE-476	ASAN	37/0/0/0	50/0/0/0	50/49/0/0	50/28/0/0	X	X	--	--	--	
	CVE-2016-8887	CWE-476	ASAN	50/3/1/0	49/24/24/0	4/2/1/0	50/17/5/0	X	X	--	--	--	
	CVE-2016-9387	CWE-190	AE	X	50/9/9/0	50/32/4/0	42/5/1/0	--	1/1/0/0	1/0/0/0	--	--	
	CVE-2016-9388	NVD-CWE-Other	AE	29/21/0/0	32/0/0/0	50/0/0/0	46/8/0/0	--	X	--	--	--	
	CVE-2016-9391	NVD-CWE-Other	AE	10/0/0/0	X	X	25/20/0/0	--	X	--	--	--	
	CVE-2016-9394	CWE-20	AE	10/0/0/0	49/2/2/0	44/0/0/0	7/0/0/0	--	--	--	--	--	
	CVE-2016-9396	NVD-CWE-Other	AE	31/11/1/0	50/0/0/0	47/32/0	489/3/0	--	X	--	50/11/0/0	50/45/0/0	
libarchive	CVE-2016-9398	CWE-617	AE	45/0/0/0	X	4/0/0/0	50/0/0/0	--	X	--	50/21/0/0	50/33/0/0	
	CVE-2016-9557	CWE-190	UBSAN	X	48/37/0/0	46/0/0/0	50/20/0/0	X	X	--	--	--	
	CVE-2016-9560	CWE-787	ASAN	3/0/0/0	2/0/0/0	49/0/0/0	50/1/0/0	X	2/1/0/0	1/1/0/0	50/13/0/0	50/32/0/0	
	CVE-2017-6850	CWE-476	ASAN	39/1/0/0	43/0/0/0	X	37/23/0/0	X	X	--	--	--	
	CVE-2016-10349	CWE-119	ASAN	46/13/0/0	44/5/4/0	50/48/0/0	X	X	X	50/19/0/0	50/49/0/0		
	CVE-2016-10350	CWE-119	ASAN	46/13/0/0	44/5/4/0	50/48/0/0	X	X	X	50/15/0/0	50/49/0/0		
	CVE-2016-5844	CWE-190	UBSAN	4/0/0/0	44/20/13/0	44/0/0/0	50/48/11/0	X	1/1/1/0	1/0/0/0	X	--	
	CVE-2017-7961	CWE-119	ASAN	2/0/0/0	47/0/0/0	43/1/0/0	50/3/0/0	X	X	X	50/9/0/0	50/0/0/0	
	CVE-2012-2806	CWE-119	ASAN	--	--	--	--	1/1/1/1	1/0/0/0	X	--	--	
	CVE-2017-15232	CWE-476	ASAN	--	--	--	--	1/1/1/1	X	--	--	--	
	CVE-2018-19664	CWE-125	ASAN	--	--	--	--	X	X	X	50/21/0/0	50/46/0/0	
	libbing	CVE-2018-8806	CWE-416	ASAN	1/0/0/0	X	50/0/0/0	19/0/0/0	X	CE	--	--	--
		CVE-2018-8964	CWE-416	ASAN	1/0/0/0	X	50/0/0/0	19/0/0/0	X	CE	--	--	--
		CVE-2016-9264	CWE-119	ASAN	9/0/0/0	50/0/0/0	45/0/0/0	50/0/0/0	1/1/1/1	CE	1/0/0/0	--	--
		CVE-2016-9265	CWE-369	ASAN	29/0/0/0	X	41/0/0/0	50/4/0/0	1/1/1/1	CE	--	50/6/0/0	50/44/16/0
CVE-2016-9266		CWE-369	UBSAN	48/0/0/0	50/0/0/0	50/1/1/0	50/0/0/0	CE	--	--	--	--	
CVE-2016-9827		CWE-119	ASAN	30/3/0/0	39/0/0/0	50/0/0/0	38/8/0/0	X	CE	X	50/22/0/0	50/0/0/0	
CVE-2016-9828		CWE-476	ASAN	12/0/0/0	21/0/0/0	42/0/0/0	50/0/0/0	X	CE	--	50/21/0/0	50/4/0/0	
CVE-2016-9829		CWE-119	ASAN	15/4/0/0	50/0/0/0	50/1/0/0	50/5/0/0	1/1/1/0	CE	1/0/0/0	--	--	
CVE-2006-2025		NVD-CWE-Other	ASAN/UBSAN	43/0/0/0	50/0/0/0	48/0/0/0	50/0/0/0	1/1/1/0	CE	--	--	--	
CVE-2010-2481		CWE-119	ASAN	34/0/0/0	50/0/0/0	50/0/0/0	49/0/0/0	X	X	X	--	--	
libbrotli	CVE-2013-4243	CWE-119	ASAN	39/3/0/0	3/0/0/0	X	X	X	X	X	50/32/0/0	50/30/0/0	
	CVE-2016-10092	CWE-119	ASAN	1/0/0/0	50/34/14/0	50/48/0/0	50/26/0/0	X	X	1/0/0/0	50/26/20/0	50/44/10/6	
	CVE-2016-10093	CWE-119	ASAN	X	42/0/0/0	46/0/0/0	50/1/0/0	TO	X	1/1/0/0	--	--	
	CVE-2016-10094	CWE-189	ASAN	1/0/0/0	18/0/0/0	45/0/0/0	50/0/0/0	X	2/0/0/0	--	50/48/25/5	50/44/15/8	
	CVE-2016-10266	CWE-369	ASAN	X	34/33/0/0	47/28/16/0	50/2/0/0	X	--	--	50/16/0/0	50/47/0/0	
	CVE-2016-10267	CWE-369	ASAN	--	--	--	--	X	1/1/0/0	--	--	--	
	CVE-2016-10268	CWE-191	ASAN	X	49/0/0/0	43/0/0/0	50/21/1/0	X	X	X	50/19/6/0	50/44/12/4	
	CVE-2016-10269	CWE-125	ASAN	--	--	--	--	X	X	1/0/0/0	--	--	
	CVE-2016-10270	CWE-125	ASAN	--	--	--	--	X	X	1/0/0/0	--	--	
	CVE-2016-10271	CWE-119	ASAN	1/0/0/0	50/34/15/0	50/48/0/0	50/26/0/0	X	X	1/0/0/0	50/30/24/0	50/44/22/6	
	CVE-2016-10272	CWE-119	ASAN	1/0/0/0	50/34/14/0	50/48/0/0	50/26/0/0	X	X	1/1/0/0	50/20/0/0	50/44/0/0	
	CVE-2016-5321	CWE-119	ASAN	X	47/0/0/0	1/1/1/0	50/24/3/1	1/1/1/1	2/2/2/1	1/1/0/0	50/25/13/0	50/43/16/11	
	CVE-2016-9273	CWE-125	ASAN	X	16/7/0/0	18/6/0/0	50/9/5/0	X	1/0/0/0	X	50/3/0/0	50/44/14/0	
	CVE-2016-9532	CWE-125	ASAN	3/0/0/0	50/16/0/0	50/44/0/0	50/3/0/0	X	X	1/0/0/0	--	--	
	CVE-2017-5225	CWE-119	ASAN	X	1/0/0/0	1/0/0/0	48/0/0/0	X	X	1/1/1/0	--	--	
libffi	CVE-2017-7595	CWE-369	UBSAN	--	--	--	--	1/1/1/1	1/1/0/0	--	50/4/0/0	50/44/0/0	
	CVE-2017-7598	CWE-369	UBSAN	5/0/0/0	45/4/0/0	38/3/0/0	44/5/0/0	X	1/0/0/0	--	--	--	
	CVE-2017-7599	CWE-20	UBSAN	--	--	--	--	X	--	--	--	--	
	CVE-2017-7600	CWE-20	UBSAN	--	--	--	--	X	--	--	--	--	
	CVE-2017-7601	CWE-20	UBSAN	--	--	--	--	1/1/1/0	--	--	50/16/0/0	50/40/0/0	
	CVE-2017-7602	CWE-190	UBSAN	27/0/0/0	50/0/0/0	X	41/0/0/0	TO	2/1/0/0	X	--	--	
	CVE-2012-5134	CWE-119	ASAN	37/0/0/0	46/0/0/0	50/0/0/0	50/0/0/0	1/1/1/1	X	X	50/0/0/0	50/49/36/29	
	CVE-2016-1838	CWE-125	ASAN	47/0/0/0	50/0/0/0	50/0/0/0	38/24/0/0	X	X	X	--	--	
	CVE-2016-1839	CWE-125	ASAN	--	--	--	--	1/1/1/1	X	X			

Table 15: Comparing patch generation capabilities of the 2 AVR tools and 2 APR tools with respect to VUL4J

Vulnerable program				AVR		APR	
ID	CVE ID	CWE ID	Compilable	Seader [146]	SeqTrans [18]	ThinkRepair [140]	SRepair [131]
VUL4J-1	CVE-2017-18349	CWE-20	✓	-	-	50/19/0/0	50/33/0/0
VUL4J-2	CVE-2017-5662	CWE-611	✓	-	-	-	50/22/11/0
VUL4J-3	CVE-2015-0263	Not Mapping	✗	-	-	-	-
VUL4J-4	CVE-2015-0264	Not Mapping	✗	-	-	-	-
VUL4J-5	APACHE-COMMONS-001	Not Mapping	✓	1/0/0/0	-	50/45/6/5	50/23/2/0
VUL4J-6	CVE-2018-1324	CWE-835	✓	1/0/0/0	50/0/0/0	50/22/6/1	40/37/6/6
VUL4J-7	CVE-2018-11771	CWE-835	✓	1/0/0/0	-	50/49/0/0	50/50/0/0
VUL4J-8	CVE-2019-12402	CWE-835	✓	1/0/0/0	-	50/42/1/0	50/32/1/0
VUL4J-9	CVE-2020-1953	Not Mapping	✓	-	-	-	43/9/7/0
VUL4J-10	CVE-2013-2186	CWE-20	✓	-	-	50/32/0/0	47/27/0/0
VUL4J-11	CVE-2014-0050	CWE-264	✓	-	-	-	50/17/8/0
VUL4J-12	CVE-2018-17202	CWE-835	✓	-	-	47/47/22/0	49/38/26/3
VUL4J-13	CVE-2018-17201	CWE-835	✓	-	-	50/33/7/0	43/30/2/0
VUL4J-14	CVE-2021-29425	CWE-20	✓	-	-	-	50/41/0/0
VUL4J-15	CVE-2016-8739	CWE-611	✗	-	-	-	-
VUL4J-16	CVE-2015-5253	CWE-264	✗	-	-	-	-
VUL4J-17	HTTPCLIENT-1803	Not Mapping	✓	-	-	50/49/0/0	40/36/0/0
VUL4J-18	CVE-2019-0225	CWE-22	✓	-	-	50/0/0/0	39/39/18/0
VUL4J-19	PDFBOX-3341	Not Mapping	✓	-	-	50/3/0/0	50/43/0/0
VUL4J-20	CVE-2018-11797	Not Mapping	✓	-	-	50/0/0/0	45/39/6/2
VUL4J-21	CVE-2014-8152	CWE-254	✓	1/0/0/0	-	-	49/6/0/0
VUL4J-22	CVE-2016-6802	CWE-284	✓	-	-	50/3/0/0	50/47/0/0
VUL4J-23	CVE-2016-5394	CWE-79	✓	-	-	-	50/45/0/0
VUL4J-24	CVE-2016-6798	CWE-611	✓	-	-	-	50/26/0/0
VUL4J-25	CVE-2017-15717	CWE-79	✓	-	-	-	50/26/0/0
VUL4J-26	CVE-2016-4465	CWE-20	✓	-	-	50/50/1/1	49/35/0/0
VUL4J-27	CVE-2014-0112	CWE-264	✓	-	-	-	49/43/33/0
VUL4J-28	CVE-2014-0113	CWE-264	✓	-	-	-	47/0/0/0
VUL4J-29	CVE-2014-0116	CWE-264	✓	-	-	-	49/42/0/0
VUL4J-30	CVE-2016-8738	CWE-20	✓	-	50/0/0/0	50/44/1/0	50/45/0/0
VUL4J-31	CVE-2016-4436	Not Mapping	✓	-	-	-	50/35/0/0
VUL4J-32	CVE-2015-1831	Not Mapping	✓	-	-	-	-
VUL4J-33	CVE-2016-3081	CWE-77	✓	-	-	-	49/28/0/0
VUL4J-34	CVE-2016-2162	CWE-79	✓	-	-	-	35/30/0/0
VUL4J-35	CVE-2014-7809	CWE-352	✓	-	50/0/0/0	-	-
VUL4J-36	CVE-2018-8017	CWE-835	✓	-	-	-	-
VUL4J-37	CVE-2015-8581	CWE-502	✗	-	-	-	-
VUL4J-38	CVE-2014-4172	CWE-74	✓	-	-	-	47/37/27/0
VUL4J-39	CVE-2018-1192	CWE-200	✗	-	-	-	-
VUL4J-40	CVE-2019-3775	CWE-287	✓	-	-	50/18/0/0	38/29/0/0
VUL4J-41	CVE-2018-1002200	CWE-22	✓	-	-	50/37/0/0	50/46/0/0
VUL4J-42	CVE-2017-1000487	CWE-78	✓	-	-	-	49/0/0/0
VUL4J-43	CVE-2018-20227	CWE-22	✓	-	-	-	36/21/2/0
VUL4J-44	CVE-2013-5960	CWE-310	✓	1/0/0/0	-	-	50/32/6/0
VUL4J-45	CVE-2018-1000854	CWE-74	✓	-	-	-	50/46/0/0
VUL4J-46	CVE-2016-3720	Not Mapping	✓	-	-	50/49/0/0	50/30/17/14
VUL4J-47	CVE-2016-7051	CWE-611	✓	-	-	50/40/12/1	48/41/22/16
VUL4J-48	CVE-2018-1000531	CWE-20	✓	1/0/0/0	-	47/40/0/0	37/34/2/0
VUL4J-49	CVE-2018-1000125	CWE-20	✓	1/0/0/0	-	-	-
VUL4J-50	CVE-2013-4378	CWE-79	✓	-	50/1/1/1	25/24/19/19	50/33/26/3
VUL4J-51	CVE-2018-1000054	CWE-918	✗	-	-	-	-
VUL4J-52	CVE-2018-1000865	CWE-269	✓	-	-	50/36/0/0	50/11/0/0
VUL4J-53	CVE-2018-1999044	CWE-835	✓	-	-	50/0/0/0	34/11/9/8
VUL4J-54	CVE-2017-1000355	CWE-502	✗	-	-	-	-
VUL4J-55	CVE-2018-1000864	CWE-835	✓	-	-	50/4/0/0	50/34/0/0
VUL4J-56	CVE-2018-1000056	CWE-918	✓	-	-	-	50/18/1/0
VUL4J-57	CVE-2018-1000089	CWE-532	✓	-	-	-	50/12/0/0
VUL4J-58	CVE-2018-1000111	CWE-863	✓	-	-	-	50/24/0/0
VUL4J-59	CVE-2015-6748	CWE-79	✓	-	-	50/37/4/3	47/38/2/2
VUL4J-60	CVE-2016-10006	CWE-79	✓	-	-	50/44/0/0	50/40/0/0
VUL4J-61	CVE-2018-1000820	CWE-611	✓	-	-	50/37/0/0	50/0/0/0
VUL4J-62	CVE-2018-18389	CWE-287	✓	-	-	50/1/0/0	47/0/0/0
VUL4J-63	CVE-2018-1000615	Not Mapping	✓	-	50/0/0/0	50/0/0/0	50/33/1/0
VUL4J-64	CVE-2018-20157	CWE-611	✓	-	-	50/8/0/0	49/31/20/0
VUL4J-65	CVE-2018-19859	CWE-22	✓	-	-	50/2/0/0	39/32/16/0
VUL4J-66	CVE-2020-1695	CWE-20	✓	-	-	50/0/0/0	50/50/0/0
VUL4J-67	CVE-2018-1274	CWE-770	✓	-	-	-	48/25/0/0
VUL4J-68	CVE-2017-8046	CWE-20	✓	-	-	-	50/24/0/0
VUL4J-69	CVE-2016-9878	CWE-22	✓	-	-	50/44/0/0	50/40/1/0
VUL4J-70	CVE-2018-15756	Not Mapping	✓	-	-	-	50/35/0/0
VUL4J-71	CVE-2018-1272	Not Mapping	✓	-	50/0/0/0	-	-
VUL4J-72	CVE-2018-15801	CWE-345	✗	-	-	-	-
VUL4J-73	CVE-2019-11272	CWE-522	✗	-	-	-	-
VUL4J-74	CVE-2019-3795	CWE-332	✗	-	-	-	-
VUL4J-75	CVE-2016-4977	CWE-19	✓	-	-	-	50/6/0/0
VUL4J-76	CVE-2018-1000850	CWE-22	✓	-	-	-	48/29/0/0
VUL4J-77	CVE-2017-1000207	CWE-502	✓	-	-	-	29/6/1/1
VUL4J-78	CVE-2019-10173	CWE-502	✓	-	-	-	48/42/0/0
VUL4J-79	CVE-2018-1002201	CWE-22	✓	-	-	-	46/41/0/0