A Multi-Dataset Evaluation of Models for Automated Vulnerability Repair

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Abstract. Software vulnerabilities pose significant security threats, requiring effective mitigation. While Automated Program Repair (APR) has advanced in fixing general bugs, vulnerability patching—a security-critical aspect of APR—remains underexplored. This study investigates pre-trained language models, CodeBERT and CodeT5, for automated vulnerability patching across six datasets and four languages. We evaluate their accuracy and generalization to unknown vulnerabilities. Results show that while both models face challenges with fragmented or sparse context, CodeBERT performs comparatively better in such scenarios, whereas CodeT5 excels in capturing complex vulnerability patterns. CodeT5 also demonstrates superior scalability. Furthermore, we test fine-tuned models on both in-distribution (trained) and out-of-distribution (unseen) datasets. While fine-tuning improves in-distribution performance, models struggle to generalize to unseen data, highlighting challenges in robust vulnerability detection. This study benchmarks model performance, identifies limitations in generalization, and provides actionable insights to advance automated vulnerability patching for real-world security applications.

Keywords: code patching · vulnerability patching · large language models · automated program repair

1 Introduction

Software vulnerabilities remain a constant threat to contemporary software systems, leaving them susceptible to exploitation by malicious actors. These vulnerabilities, which include problems like injection flaws and memory management errors, can result in unauthorized access, data breaches, and service interruptions [33]. Addressing these issues is essential to ensure the reliability and security of software systems [1]. However, the manual effort required to detect and fix these vulnerabilities is time-consuming, prone to errors, and struggles to match the growing complexity and scale of today's software ecosystems [23].

Automated Program Repair (APR) has gained traction as a promising approach to tackle this issue, employing computational methods to autonomously generate fixes for software bugs [3]. While APR has achieved notable progress in addressing general software defects, the specialized area of vulnerability-focused program repair—which deals with the unique challenges of security vulnerabilities—remains underdeveloped. Unlike general-purpose bug fixes, patches for vulnerabilities often require addressing the flaw in a way that is not only functionally correct but also generalizable across variations of the vulnerability [9]. This makes vulnerability patching a more nuanced subset of Automated Program Repair (APR), where the ability to generate broadly applicable fixes becomes especially important.

Existing techniques in vulnerability-focused Automated Program Repair (APR) predominantly depend on either static analysis tools or traditional machine learning models trained on specific vulnerability patterns. Although these approaches have demonstrated potential in identifying vulnerabilities, their capacity to generate meaningful and effective patches remains limited. For instance, static analysis tools are highly effective at detecting vulnerabilities but often struggle to produce practical fixes [35]. Similarly, conventional machine learning models are hindered by their dependence on restricted datasets [14], which limits their generalizability and effectiveness across a wide range of programming languages and vulnerability types [37].

Recent advancements in deep-learning have paved the way for automated vulnerability patching, particularly with the emergence of pre-trained language models tailored for code. Models like CodeBERT[12] and CodeT5[38] utilize large-scale code corpora to capture both syntactic and semantic structures, facilitating tasks such as code generation, summarization, and translation [17]. Their ability to discern patterns from extensive datasets makes them a promising tool for vulnerability-focused program repair. However, the practical application of these models remains challenging. Due to substantial differences in syntax, semantics, and vulnerability characteristics across programming languages, existing pre-trained models, which are often designed for monolingual or domain-specific tasks, may struggle with generalization [8]. Evaluating their performance across diverse languages is therefore a crucial yet underexplored area of research [19].

This paper systematically evaluates the performance of pre-trained language models in vulnerability-focused program repair, specifically analyzing CodeBERT and CodeT5 in generating patches for known vulnerabilities across six datasets covering four programming languages. We assess their effectiveness using *CodeBLEU* and *CrystalBLEU* scores and explore their generalizability by evaluating performance on both in-distribution and out-of-distribution datasets, providing insights into their strengths and limitations.

Our results show that while both models excel in generating vulnerability patches, they exhibit distinct limitations. CodeT5 generally outperforms CodeBERT in accuracy, especially on datasets with complex vulnerability patterns. However, both models struggle with fragmented contexts and sparse data, which limits their ability to produce correct fixes in such settings. Additionally, while fine-tuning improves performance on in-distribution datasets, both models face challenges in generalizing to out-of-distribution datasets, highlighting limitations in detecting and patching vulnerabilities in unseen scenarios.

Hence, our contributions in this paper are threefold:

- We provide an evaluation of CodeBERT and CodeT5 for vulnerability-focused program repair, covering a diverse set of 6 datasets across multiple programming languages.
- We establish benchmarks for model performance in generating vulnerability patches, serving as a foundation for evaluating pre-trained models in dataset-driven vulnerability patching scenarios.
- We identify key limitations in model generalization, particularly the challenges of fine-tuning and performance on out-of-distribution datasets.

2 Related Work

Software vulnerabilities refer to security gaps or defects within code that can be leveraged by malicious actors to compromise systems [32]. One notable example is the buffer overflow vulnerability, which arises when a program tries to write more data into a buffer than it can hold, leading to the overflow spilling into neighboring memory areas. This can allow attackers to inject and execute harmful code [18]. As these vulnerabilities grow more complex, they pose substantial obstacles to developing and deploying robust countermeasures.

While vulnerability detection has been extensively studied, significantly less attention has been given to generating patches. Traditional static analysis tools have long been used for detection, but their reliance on predefined rules often makes it difficult to identify complex patterns [2]. In contrast, AI-driven methods have gained traction for their ability to process vast codebases and uncover intricate security flaws. Models like *CodeBERT*[13] and *GraphCodeBERT*[21] have proven effective in analyzing source code, contributing to advancements in vulnerability detection and assessment [16]. Additionally, large language models (LLMs) such as OpenAI's GPT-4, Meta AI's Llama2, and Mistral AI's Mistral have demonstrated strong adaptability in tackling vulnerability detection tasks [22].

Conversely, creating effective patches continues to be a significant challenge. The majority of research on automated patch generation is centered on fixing general code defects rather than targeting vulnerabilities directly. The subsequent sections will explore methodologies within this broader context.

2.1 Traditional Approaches to Code Repair

Automated code repair traditionally falls into two categories: heuristic-based and constraint-based [20]. Heuristic methods search for patches that pass all tests, often using transformation schemas for efficiency [28]. Approaches like GenProg [27] and PAR [26] leverage genetic programming, while others use random or deterministic strategies to refine the search.

Constraint-based methods employ symbolic execution [5] to guide patch generation by exploring multiple execution paths. Tools such as SemFix [30] and Angelix [29] derive repair constraints, while techniques like Nopol [40] target specific cases, such as repairing conditional expressions.

2.2 ML-Based Code Repair

Machine learning has emerged as a key technique for automating code repair, generating patches for software vulnerabilities and bugs. Early efforts relied on Neural Machine Translation (NMT) with encoder-decoder architectures, such as SequenceR [7] and CODIT [6], which used attention mechanisms to prioritize critical regions during decoding.

More recently, transformer-based models have excelled at capturing long-range dependencies and nuanced context, leveraging attention to focus on relevant code segments. Ding *et al.* [10] highlighted their transformative potential, paving the way for broader adoption in program repair.

Further expanding these approaches, large language models (LLMs) such as CodeBERT [12] and CodeT5 [38] have shown promise for code-related tasks, benefiting from pretraining on large code corpora. While prior work has explored their capabilities in general code generation and repair, their effectiveness for vulnerability-specific patching remains underexplored. This motivates our evaluation of both models in this context.

Nevertheless, patching vulnerabilities is distinct from fixing general bugs. It requires highly contextual, security-focused modifications and robust generalization across complex scenarios. Current solutions emphasize fine-tuning LLMs and advancing techniques to enhance adaptability for various datasets and security-specific demands.

3 Methodology

In this section, we outline our experimental workflow, from dataset preparation and preprocessing to splitting the data for training and testing, followed by model selection and fine-tuning strategies.

3.1 Dataset Preparation and Pre-processing

For this study, we collected six publicly available datasets containing code samples with known vulnerabilities and their corresponding patches. These datasets comprises of multiple programming languages, including Go, Java, PHP, and C, ensuring diverse code structures and vulnerability patterns. The inclusion of diverse datasets allowed us to evaluate the models' ability to generalize across varied programming contexts. Details about these datasets, including their references are provided in Section 4.1, offering a comprehensive overview of their sources. This diversity in datasets not only enhances the robustness of our evaluation but also reflects real-world scenarios where vulnerabilities span multiple languages and coding paradigms.

We preprocessed the raw datasets to standardize their structure and enhance model compatibility. Given the noise in real-world vulnerability datasets [14,25], our preprocessing aimed to reduce inconsistencies and improve data quality, as emphasized in studies on noisy datasets [24,15]. By ensuring uniformity, we created a robust foundation for reliable model training and evaluation. These steps were critical for noise reduction and dataset preparation.

i. **Token Length Filtering.** Code exceeding *512* tokens was truncated/excluded due to model limits.
ii. **Comment Removal.** Language-specific regex removed comments, focusing on functional code.
iii. **Normalization.** Fixed formatting inconsistencies (whitespace, line breaks) for uniform datasets.

Table 1: Datasets

Dataset	I_{rows}	$R_{tok.}$	$R_{comm.}$	$R_{norm.}$	T_{rows}
Go	1,472	551	357	0	921
PHP	6,696	335	4,923	1	6,360
MegaVul_C_2023	17,975	3,147	0	302	14,526
MegaVul_C_2024	17,975	3,147	0	302	14,526
Vul4J	1,790	3	0	0	0
CodeParrot	69,420	19,420	1,505	0	50,000

3.2 Training and Testing Split

The datasets were partitioned into *85%* for training and *15%* for testing, a widely adopted ratio that provides a robust balance between model learning and evaluation [41]. This split ensures sufficient data for effective training while reserving enough samples to yield meaningful test results. To avoid data leakage and maintain the integrity of the evaluation, all overlapping or duplicate instances were excluded.

3.3 Model Selection and Fine-Tuning

We utilized and fine-tuned *CodeBERT* and *CodeT5* for vulnerability patching, leveraging their strengths in code understanding and generation. CodeBERT, tailored for programming tasks, adapted to detect vulnerabilities and their fixes, while CodeT5, optimized for code generation, improved handling diverse code structures. Despite alternatives like *TFix*, these models were chosen for their versatility, robustness, and real-world applicability.

4 Experimental Setup

In this section, we detail the computational environment and methodologies used for training and evaluating our models on a range of vulnerable code scenarios.

Table 2: Accuracy Scores

	CodeBLEU		CrystalBLEU	
Dataset	*CodeBERT*	*CodeT5*	*CodeBERT*	*CodeT5*
Go	0.7641	0.6499	0.6557	0.5264
PHP	0.7351	0.6924	0.4624	0.3727
MegaVul_C_2023	0.8396	0.8549	0.7893	0.8131
MegaVul_C_2024	0.8395	0.8549	0.7893	0.8131
Vul4J	0.3737	0.9373	0.1229	0.8985
CodeParrot	0.997	0.9973	0.9595	0.9603

All experiments were conducted on a High-Performance Computing (HPC) cluster with nodes featuring *2.20GHz Intel Xeon Silver 4210* processors and *NVIDIA Tesla V100-PCIE-32GB* GPUs. Model training and evaluation were performed using the *PyTorch 2.0.1* framework with *CUDA 12* compatibility.

4.1 Datasets

To address the research questions outlined in Section 5, we leveraged publicly available datasets that contain comprehensive collections of vulnerable source code along with their corresponding fixed versions, which served as our ground truth. Specifically, we utilized six datasets, including Go and PHP [1], MegaVul_C_2023, and MegaVul_C_2024 [2] [31], Vul4J[3][4], and also CodeParrot [4]. These datasets encompass a variety of programming languages, including C, Java, Go, and PHP, offering a well-rounded foundation for evaluation. Prior to their use, we implemented preprocessing steps as outlined in Section 3.1

Table 1 reports on the size of our datasets, in terms of the number of rows (I_{rows}), rows affected by tokenization ($R_{tok.}$), rows affected by comment removal ($R_{comm.}$), rows affected by normalization ($R_{norm.}$), and the total number of rows remaining after pre-processing ($T_{rows.}$).

4.2 DL Models

For vulnerability patching, we employed *CodeBERT*[12] and *CodeT5*[38], widely used for code analysis and vulnerability detection due to their strong performance in handling code semantics and structure.

CodeBERT[12] bridges programming and natural languages, enhancing tasks like code completion, summarization, and vulnerability detection. Built on a transformer architecture, it captures syntactic and semantic relationships from

[1] Go and PHP–`https://doi.org/10.5281/zenodo.13870382`
[2] MegaVul_C_2023, and MegaVul_C_2024–`https://github.com/Icyrockton/MegaVul`
[3] Vul4J–`https://github.com/tuhh-softsec/vul4j`
[4] `https://huggingface.co/datasets/codeparrot/github-code-clean`

code–language pairs, enabling precise vulnerability identification and remediation at scale.

CodeT5[38] is a T5-based model for code generation and understanding, excelling in vulnerability detection and patching. It generates context-aware patches, preserves code intent, and supports multiple languages. Pre-trained on extensive programming data, it performs well on benchmarks, improving software security and code quality. It also preserves semantics in decompilation, advancing vulnerability repair frameworks [39].

4.3 Evaluation Metrics

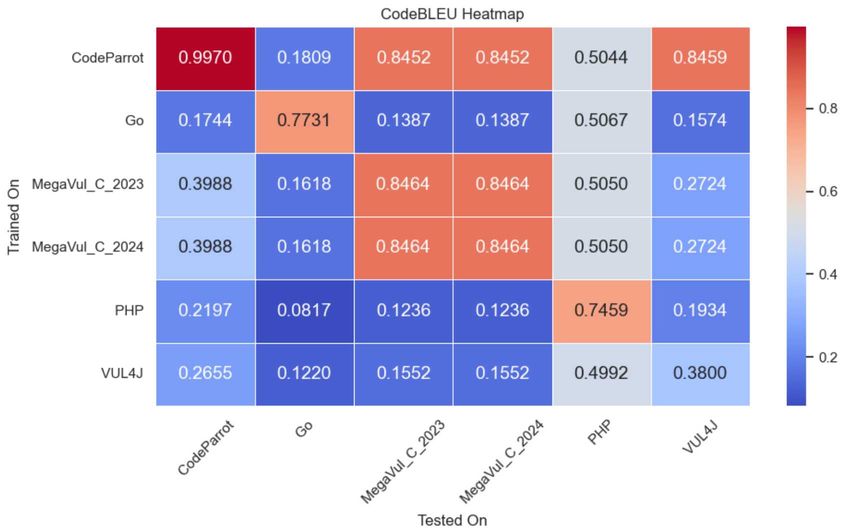
We evaluated the LLMs using *CrystalBLEU*[11] and *CodeBLEU*[36]. CrystalBLEU refines BLEU [34] by addressing n-gram limitations in programming languages, focusing on trivially shared n-grams for better code evaluation. CodeBLEU enhances BLEU by combining n-gram matching with AST-based structures and semantic data flow, making it ideal for assessing code quality. Together, these metrics provide accurate evaluations by considering both syntactic and semantic aspects of generated code.

5 Results

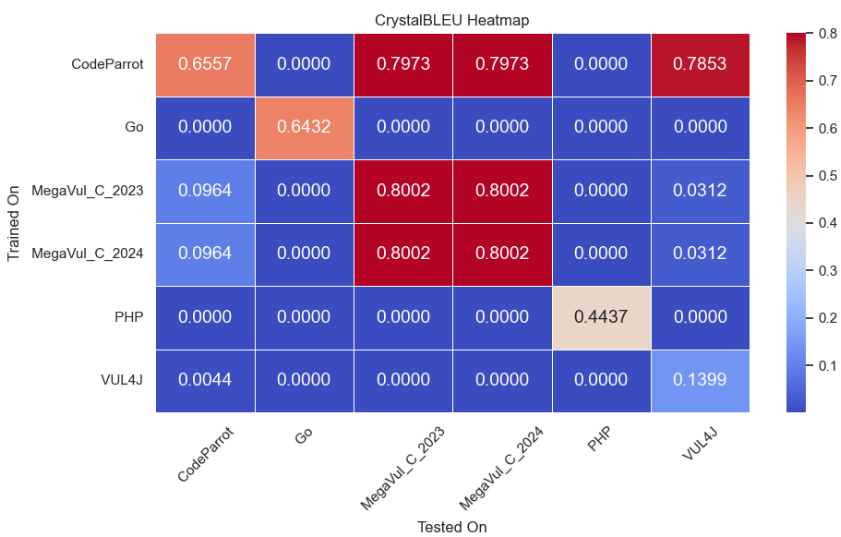
In this section, we present our findings, focusing on how effectively CodeBERT and CodeT5 generate accurate patches for both known and unknown vulnerabilities across diverse datasets.

5.1 RQ1: How effectively do CodeBERT and CodeT5 generate accurate patches for known vulnerabilities across diverse datasets?

In this research question, we evaluated the effectiveness of CodeBERT and CodeT5 in generating patches by fine-tuning them on the same dataset. Our analysis spans six datasets across four programming languages, following the methodology outlined in Section 3.2. **Table 2** displays the CodeBLEU, and CrystalBLEU scores of CodeBERT and CodeT5 across six datasets used in our evaluation. Examining the performance of both models on these datasets reveals key insights into how pre-training data diversity and model architecture impact the models' effectiveness in vulnerability patching tasks. CodeT5 consistently outperforms CodeBERT in VUL4J and CodeParrot datasets, with less difference on MegaVul_C_2023 and MegaVul_C_2024 datasets but still demonstrates a clear advantage over CodeBERT when evaluated using both CodeBLEU and CrystalBLEU accuracy scores. This result aligns with the fact that CodeT5 has been pre-trained on diverse data that spans a variety of programming languages and textual formats, enabling it to capture more generalized patterns and nuances in code. On Go, and PHP, CodeBERT performs better than CodeT5 using

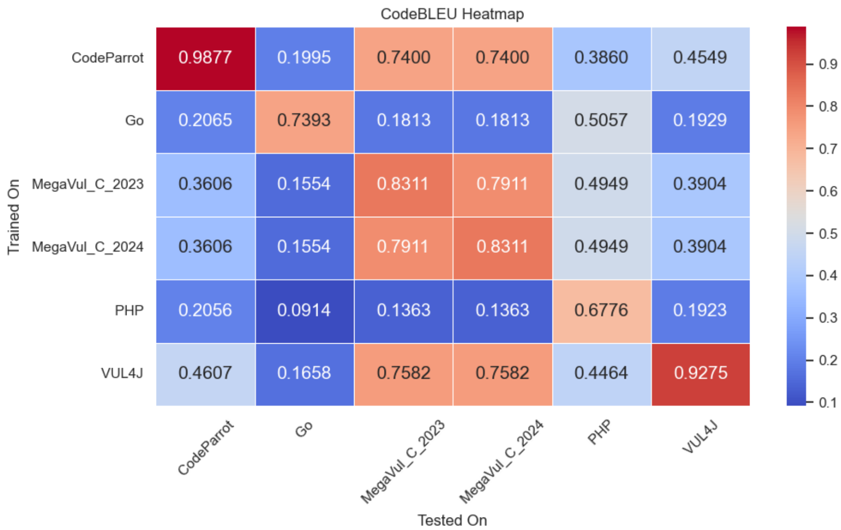


(a) CodeBLEU for CodeBERT

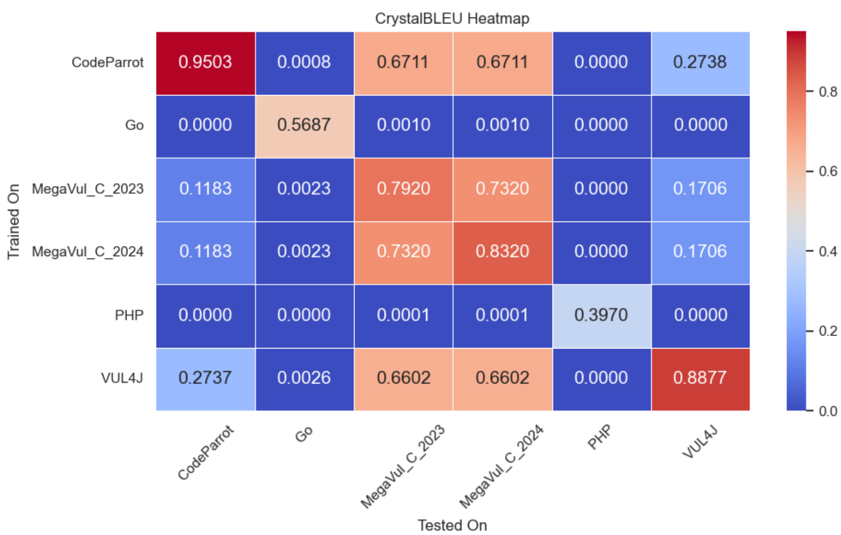


(b) CrystalBLEU for CodeBERT

Fig. 1: Heatmaps for CodeBERT



(a) CodeBLEU for CodeT5



(b) CrystalBLEU for CodeT5

Fig. 2: Heatmaps for CodeT5

CodeBLEU and CrystalBLEU metrics. By analyzing these two datasets, we observed that they often contain incomplete functions or isolated snippets lacking full context. This could potentially lead to lower performance for CodeT5, as it relies on contextual understanding from diverse sources that might not align well with fragmented or incomplete code. Conversely, CodeBERT, which is also trained on a broad variety of programming languages, may still benefit from its fine-tuned focus on code structure, making it more adaptable to such fragments.

These findings suggest that CodeBERT's architecture might be inherently more robust when handling incomplete or context-limited code, a factor that could contribute to its better performance on Go and PHP. Moreover, despite CodeBERT generally being outperformed by CodeT5, the lacking the extensive pre-training diversity of CodeT5, can still achieve near-competitive results in certain domains, particularly for language-specific tasks. This observation underscores the need for further investigation to better understand the interplay between dataset characteristics and metric sensitivity, rather than drawing generalized conclusions about the performance of CodeBLEU or CrystalBLEU.

Our results highlight the benefits of model diversity in deep learning-based vulnerability patching. CodeT5's broad pre-training excels on datasets with complex vulnerabilities, while CodeBERT's focused design performs well on datasets with more traditional, syntactically constrained samples. These insights show that model choice should depend on dataset characteristics. CodeBERT's simpler architecture likely makes it less reliant on context, while CodeT5 handles diverse inputs more effectively. Thus, while CodeT5 is suited for complex, varied data, CodeBERT is valuable in environments with incomplete or non-standard code snippets.

5.2 RQ2: How effectively do CodeBERT and CodeT5 generate accurate patches for `unknown` vulnerabilities across diverse datasets?

Figures 1 and 2 show the results for RQ2, where we evaluated the fine-tuned CodeBERT and CodeT5 models. For each model, we fine-tuned them on one dataset and tested their performance on two types of datasets: (1) the same dataset used for fine-tuning (in-distribution testing) and (2) all remaining datasets that were not used during fine-tuning (out-of-distribution testing). This setup allowed us to analyze whether fine-tuning pre-trained models (i.e., CodeBERT and CodeT5) on high-quality datasets enhances their ability to detect vulnerabilities, including previously unknown ones. Specifically, we aimed to determine if fine-tuning improves the models' generalization capabilities compared to their pre-trained versions, both on datasets they were trained on and on unseen datasets.

In Section 5.1, we demonstrated the performance of pre-trained models (CodeBERT and CodeT5) in detecting vulnerabilities accurately on datasets they were trained or fine-tuned on. For RQ2, we extended this analysis to evaluate their performance on both in-distribution and out-of-distribution datasets. From Figure 1 and Figure 2, we observe that both models perform significantly better on in-distribution datasets, with almost similar results and only minor percentage differences compared to their performance in Section 5.1 or RQ1. This behavior is expected, as fine-tuning allows models to adapt to the specific characteristics of the training data, leading to higher accuracy on familiar datasets.

However, when tested on out-of-distribution datasets, the models exhibit a noticeable drop in accuracy. Notably, when a model trained on a specific programming language is tested on the same language—for example, trained on Megavul_C_2023 and tested on Megavul_C_2024—the accuracy remains high. A similar trend is observed for Vul4J and CodeParrot, as both are Java-based datasets. In contrast, for CodeBERT, training on Vul4J and testing on Vul4J results in lower accuracy. This is due to the same reason mentioned in Section 5.1. These findings suggest that while fine-tuning enhances performance on datasets similar to the training data, it does not generalize well to entirely new datasets.

Additionally, the models exhibit non-deterministic behavior (e.g., small variations in accuracy even on in-distribution datasets), which is common in large language models (LLMs) like CodeBERT and CodeT5. This variability can be attributed to factors such as randomness in weight initialization, optimization processes, or inherent fluctuations in the models' predictions.

6 Discussion

Fine-tuning on well-characterized datasets substantially boosts CodeBERT and CodeT5 performance in in-distribution tests. However, this advantage drops sharply on out-of-distribution data, especially when the code differs in language or structure. Such declines reflect overfitting, as models learn dataset-specific signals rather than broader security principles.

Additionally, we observe sporadic variability across executions, caused by random weight initialization and hyperparameter sensitivity. Repeated training can alleviate these fluctuations, but consistent checkpointing and parameter tuning remain critical for stable outcomes.

A key lesson is that diverse datasets foster more generalizable repair models. Narrow data coverage may yield high accuracy for certain vulnerability types but struggles with unseen threats. Beyond standard fine-tuning, future work could explore meta-learning, multi-task strategies, and data augmentation to improve cross-domain robustness and ensure patches address genuine security concerns.

7 Threats to Validity

Construct Validity. We evaluate "correct" patches using CodeBLEU and CrystalBLEU, which primarily gauge syntactic and limited semantic cues. Although these metrics are well-suited for code-focused tasks, they may overlook deeper security implications and potential exploit vectors. Moreover, the labeled "patched" instances within our datasets may not fully represent truly secure fixes, raising the risk of overestimating model performance.

Internal Validity. Our findings are sensitive to model randomness (e.g., weight initialization) and hyperparameter settings. Even minor fluctuations in these variables can skew comparative outcomes. Additionally, data preprocessing steps such as token truncation and comment removal may eliminate vital context needed to generate security-relevant patches. These factors, if not uniformly controlled, limit the consistency and interpretability of our experimental results.

External Validity. While this work involves six datasets in four languages, real-world projects frequently rely on specialized libraries and domain-specific coding styles. The observed performance drop on out-of-distribution datasets highlights limited cross-domain generalizability. To enhance broader applicability, future work should consider more diverse datasets and investigate meta-learning approaches that better capture variability across language ecosystems and security contexts.

8 Conclusion

Our findings illustrate the promise of large language models for automated vulnerability repair while underscoring significant generalization challenges. CodeBERT and CodeT5 both excel when confronted with familiar vulnerability patterns, yet exhibit performance gaps on unseen datasets and in cross-language contexts. Achieving robust, production-grade vulnerability repair will demand more than simple fine-tuning; it calls for richer datasets, more advanced training paradigms, and continuous adaptation to evolving security threats. By addressing these gaps, future research and practice can more confidently integrate automated patch generation into real-world software development pipelines.

9 Data Availability

In support of Open Science, our datasets and code are being finalized for public release on Zenodo. A persistent DOI will be provided here shortly.

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