LLM4CVE: Enabling Iterative Automated Vulnerability Repair with Large Language Models

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Abstract

Software vulnerabilities continue to be ubiquitous, even in the era of AI-powered code assistants, advanced static analysis tools, and the adoption of extensive testing frameworks. It has become apparent that we must not simply prevent these bugs, but also eliminate them in a quick, efficient manner. Yet, human code intervention is slow, costly, and can often lead to further security vulnerabilities, especially in legacy codebases. The advent of highly advanced Large Language Models (LLM) has opened up the possibility for many software defects to be patched automatically. We propose LLM4CVE an LLM-based iterative pipeline that robustly fixes vulnerable functions in real-world code with high accuracy. We examine our pipeline with State-of-the-Art LLMs, such as GPT-3.5, GPT-4o, Llama 3 8B, and Llama 3 70B. We achieve a human-verified quality score of 8.51/10 and an increase in groundtruth code similarity of 20% with Llama 3 70B. To promote further research in the area of LLM-based vulnerability repair, we publish our testing apparatus, fine-tuned weights, and experimental data on our website¹.

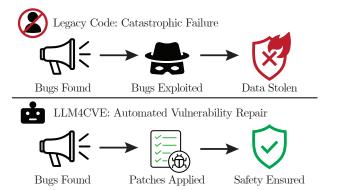


Figure 1: How LLM4CVE assists in preventing bug exploitation

1 Introduction

Human developers are prone to costly mistakes when designing software systems. Often, these are not simple errors, but a fundamental misunderstanding of cybersecurity concepts [1]. These vulnerable programs are targets for criminals to steal credentials, assets, and other valuable items from end-users [2]. Moreover, the frequency of these types of attacks is steadily increasing [3]. As a result, the ability to quickly and efficiently rectify software bugs has become more critical than ever before.

Already, we have seen the significant impacts of

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¹https://sites.google.com/view/llm4cve

these bugs – billions of dollars in lost economic value [4, 5, 3], countless man-hours spent on bug resolution [6], and the leakage of sensitive user data to malicious actors [7, 8]. Cyberattacks – like the one done to the company SolarWinds in 2020 [9] – are an example of this phenomenon. This attack infiltrated computers in both the U.S. government and private sector, leading to the leakage of millions of classified and confidential documents to foreign adversaries.

The proliferation of cyberattacks is not simply limited to one specific application domain. The Internet-of-Things (IoT) revolution has led to the adoption of embedded systems in an ever-growing variety of devices [10]. However, these systems are dangerously prone to critical security vulnerabilities [11, 12, 13]. An attacker could feasibly extract personal information or confidential credentials by exploiting these bugs. Many such attacks have been deployed in the real world, leading to the proliferation of botnets [14] and power grid disruptions [15]. As manufacturers race to incorporate new devices and features into their IoT products – often without regard for the security and privacy of the end user – these types of attacks are poised to proliferate in the future.

Even worse, autonomous vehicles are also vulnerable to many types of common security vulnerabilities [16]. These types of bugs are even more serious, as errors in control software can endanger the lives of pedestrians, passengers, or other drivers. While automatic testing suites have been created to verify the robustness of these autonomous systems in the physical world [17], they are still prone to traditional software-driven attacks, much like any other safety-critical computer system. Therefore, these vehicles must be secured against vulnerabilities and bugs.

The shared link between the aforementioned vulnerable systems is their usage of common open-source software – often written in C. These massive projects – like the Linux kernel [18], OpenSSL [19], and FFmpeg [20] – are frequently targeted by hackers. As a result, these large software projects contain a disproportionate amount of Common Vulnerabilities and Exposures (CVEs) [21]. A CVE informs the public about a known security vulnerability and serves as a centralized repository of information regarding the exploit [22]. However, a CVE entry does not facil-

itate the automated repair of vulnerabilities on its own.

Several existing methods have been created to patch vulnerable software with minimal human input [23, 24, 25, 26, 27, 28]. These techniques allow for the rectification of costly bugs with a comparatively lesser human cost. Yet, even these advanced systems are prone to mistakes. While these techniques often help rectify real-world bugs, automated vulnerability repair methods are known to generate invalid code [29] or introduce additional bugs [30]. More pressingly, these techniques often require analysis from a developer experienced with the program's codebase to fully implement [31]. This presents challenges when security vulnerabilities are identified in old, unmaintained code – or where the subject-matter experts for a particular product are no longer accessible. As a result, cybercriminals would be able to exploit these bugs, potentially leading to the leakage of sensitive user data. We demonstrate in Figure 1 how our pipeline can mitigate the risks caused by abandoned or poorly maintained legacy code.

As an increasing amount of software governs critical real-world systems, the importance of program maintenance has grown drastically. The proportion of engineers devoted to maintaining legacy code systems has risen significantly [32]. Even then, the average time-to-fix of software vulnerabilities is only increasing [33]. This presents a growing threat to endusers, especially when these bugs may take far longer to be patched in downstream code.

The advent of highly capable Large Language Models (LLMs) has the potential to transform how software vulnerabilities are rectified, especially in older codebases. However, it is known that LLMs often produce flawed, uncompilable code [34]. Even then, state-of-the-art LLMs such as GPT-40 [35] and Llama 3 [36] have spurred significant changes in software engineering practices. Moreover, specialized models tuned for code generation have appeared [37], further increasing the potential for automated software augmentation and creation. Techniques such as Parameter-Efficient Fine-Tuning (PEFT) [38] and Low-Rank Adaptations (LoRAs) [39] extend the capabilities of these models, leading to an increase in performance while simultaneously streamlining the

model training process [40, 41]. More recently, models incorporating a Mixture-of-Experts (MoE) have enabled significant gains in LLM performance [42]. Researchers have also studied Prompt Engineering – a method of refining LLM input to measurably improve the relevancy, accuracy, and quality of responses [43, 44, 45]. These advances in Large Language Models have created a unique opportunity for combination with existing vulnerability repair techniques to automatically rectify common software bugs.

We introduce LLM4CVE, an iterative pipeline that integrates Large Language Models with alreadyexisting CVE data to fix common classes of software vulnerabilities with minimal human input. Given a snippet of code identified as faulty, our pipeline iterates until a viable candidate is obtained. LLM4CVE begins generating a candidate fix, evaluating the viability of the fix, and applying required changes to increase the viability of the synthesized code. This iterative loop is further enhanced by the incorporation of LoRA fine-tuning into our pipeline. We also use prompt engineering to create a set of optimized prompts to enhance the quality of the generated code. Ultimately, LLM4CVE is capable of synthesizing a viable replacement code snippet, automating the vulnerability repair process for real-world examples of candidate CVEs. We summarize our key contributions as the following:

- We present a novel, automated method for fixing security vulnerabilities in real-world programs that require minimal intervention from a skilled domain expert. Moreover, our approach is capable of preserving application security even in codebases with a small number of experienced maintainers.
- To the best of our knowledge, we create the first automated, iterative process for a Large Language Model to systematically correct vulnerabilities in code, improving on current automated vulnerability correction tools.
- We present a detailed study of the effectiveness of our iterative pipeline for fixing various

classes of CVE/CWEs across multiple foundational models. Our methodology is tested on several mainstream LLMs – including GPT-3.5, GPT-40, Llama 3 8B, and Llama 3 70B.

The remainder of this paper is organized as follows: in Section 3, we examine existing approaches to vulnerability repair - including both manual and automated solutions. A discussion of the benefits of LLM4CVE over the current State-of-the-Art works follows. Next, we provide the reader with a brief background on both Large Language Models and automated vulnerability repair in Section 2. We discuss the foundations of LLMs and the methods for finetuning them, as well as general methods of repairing software vulnerabilities without human intervention. A presentation of the LLM4CVE methodology follows in Section 4, where each pipeline stage is thoroughly detailed. Our experimental setup and results are then displayed in Sections 5 and 6. Finally, Sections 7, and 8 discuss the potential applications of our findings, known limitations and future improvements. The paper concludes with a public release of the LLM4CVE pipeline in Section 9.

2 Background

The LLM4CVE pipeline builds upon accepted wisdom in the field of Automated Vulnerability Repair, as well as incorporating state-of-the-art LLM augmentations – including Parameter-Efficient Fine-Tuning (PEFT) and Low-Rank Adaptations (LoRAs) – while also incorporating more traditional LLM techniques such as Prompt Engineering. In this section, we provide the reader with sufficient background knowledge for each domain, while also providing context for the design choices implemented in our pipeline.

2.1 CVEs & CWEs

The reporting of bugs to centralized online repositories has become increasingly common. Entities such as the National Vulnerability Database [46] and MITRE's Common Vulnerabilities and Exposures [22] provide up-to-date access to bug reports

and mitigation measures. Often, when a security vulnerability is discovered in widely-used software, a description is listed on one or more of these databases [2]. Since CVEs often target a specific software problem instead of describing a broad vulnerability class, the Common Weakness Enumeration (CWE) system was created to fulfill this purpose [47]. Ultimately, both the CVE and CWE identifiers are useful in our analysis for rectifying vulnerabilities.

2.2 Vulnerability Analysis & Repair

The common goal of every vulnerability repair technique is to in some way rectify underlying software bugs that would otherwise lead to undefined or unsafe behavior. While formal models defining types of software deficiencies – such as faults, errors and failures – exist [48], we focus on the most simple definition – the detection and repair of problems that result in unexpected output.

Automated vulnerability detection and repair often targets a specific class of bugs [49, 50]. This may be due to their heightened potential for exploitation, frequency in real-world code, or their ease of detection and subsequent patching, among other factors. These classes are commonly represented in CVEs and CWEs, as explained in Section 2.1.

Common characterizations of vulnerability repair break the process into three sections – (1) bug detection, (2) patching, and (3) patching [23]. The detection phase involves scanning source code using static analyzers [51], machine learning [52, 53], or other methods [54]. Here, potentially faulty sections of code are identified for correction. Next, the deficient code is rectified through a variety of algorithmic [49] and deep-learning [24] methods. Before the patch is complete, a verification stage must confirm the reliability and robustness of the fix. This is often done through validation with a test suite [55, 29], static analysis [56], or by expert verification [57].

These methods are similar to industry-standard best practices regarding the software vulnerability life cycle [58]. An overview of these practices and how LLM4CVE is positioned in this cycle is shown in Figure 2.

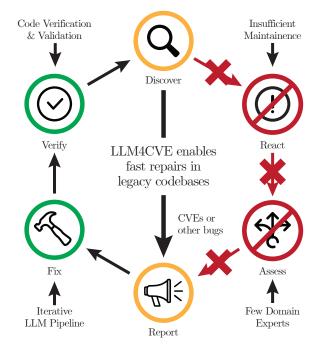


Figure 2: Rectification of software vulnerabilities often follows a predefined cycle, which LLM4CVE augments for faster turnaround times

2.3 Large Language Models

Large Language Models (LLMs) leverage the attention mechanism [59] to efficiently process complex inputs, capturing syntax and structure to understand dependencies between spatially distant but semantically linked tokens [60, 61]. Methods like Retrieval-Augmented Generation further enhance these models by referencing external knowledge bases during inference to improve factual accuracy [62].

The success of OpenAI's GPT series [35] has fueled the rise of LLMs, with parameter counts growing exponentially—from GPT-3's 175 billion parameters [63] to GPT-4's theorized 1.76 trillion [64]. This scaling increases performance and may lead to emergent abilities [65], though the full impact is not yet fully understood [66].

However, many leading LLMs, including those from OpenAI, are not open-source, posing challenges for fine-tuning and raising data privacy concerns.

While OpenAI offers a fine-tuning API, it is restrictively licensed and costly [67]. Consequently, several open-source LLMs have emerged, such as Llama 3 [36], Code Llama [37], and Mixtral (MoE) [42].

2.3.1 LLM Augmentation

To enhance LLM capabilities across diverse tasks, two key augmentation methods are used: (1) Parameter-Efficient Fine-Tuning/Low-Rank Adaptation (PEFT/LoRA), and (2) Mixture-of-Experts.

The vast size of modern LLMs demands substantial computational resources for training. Parameter-Efficient Fine-Tuning (PEFT) addresses this by simplifying the fine-tuning process [68, 69, 70]. A prominent PEFT method is Low-Rank Adaptation (LoRA), which freezes most model parameters and fine-tunes using injected rank decomposition matrices [39]. Further improvements come from quantization [71] and applying LoRAs to Mixture-of-Experts models [72]. A description of the LoRA training process is given in Figure 3.

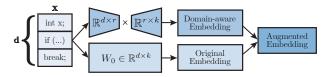


Figure 3: LoRAs enable the fine-tuning of LLMs with a comparatively low computational cost

Another method is the Mixture-of-Experts (MoE) paradigm, which trains multiple specialized "expert" models and uses a router to select the optimal ones during inference [73]. MoE models have demonstrated better scalability [74] and performance compared to compute-equivalent single-expert models [75].

2.3.2 Prompt Engineering

The quality of an LLM's output is directly influenced by the prompt quality. Refining prompts, known as *Prompt Engineering*, improves performance on tasks like logic problems [45], object annotation [76], and

general reasoning [77]. Techniques such as Chainof-Thought reasoning break down complex processes into individual steps for the LLM [78]. We employ a similar approach in the LLM4CVE pipeline, using automated compiler and metric-based feedback. LLMs can also perform zero-shot reasoning by being prompted to think step-by-step [79].

3 Related Works

Our work builds upon three primary areas: (1) automated vulnerability repair, (2) code generation with Large Language Models (LLMs), and (3) vulnerability detection and repair using LLMs. We integrate recent advancements in these fields to enhance the robustness and viability of our proposed pipeline, *LLM4CVE*.

3.1 Classical Automated Vulnerability Detection Repair

Interest in automatically rectifying software vulnerabilities has been strong for decades. Traditional methods have leveraged program analysis tools, such as compilers or static analysis toolchains, to assist in fixing software bugs [24, 23, 29, 30, 31, 49, 80]. However, static analysis has limitations in detecting certain types of bugs, such as those involving the Java Reflection API [81].

Advanced techniques have been developed to address these limitations. For example, methods using Generative Adversarial Networks (GANs) have been effective for vulnerability repair without the need for labeled training examples [28]. However, these methods are often evaluated only on synthetic code samples rather than real-world vulnerabilities.

Transfer learning has also been explored for automated software repair. The *VRepair* framework demonstrated significant improvement over state-of-the-art methods, achieving almost a 50% increase in repair rate using transformer architectures [82]. Despite its success, the model used is significantly smaller than modern LLMs like GPT-4 [35].

Vision Transformers have been utilized to rectify code vulnerabilities by using special queries to locate

Table 1: An overview of selected CWEs for the LLM4CVE pipeline

CWE	Title	Count
CWE-125	Out-of-bounds Read	452
CWE-119	Improper Restriction of Operations within the Bounds of a Memory Buffer	363
CWE-20	Improper Input Validation	289
CWE-787	Out-of-bounds Write	179
CWE-476	NULL Pointer Dereference	176
CWE-190	Integer Overflow or Wraparound	156
CWE-120	Buffer Copy without Checking Size of Input ("Classic Buffer Overflow")	121
CWE-416	Use After Free	120

vulnerable code snippets and generate accurate repair suggestions [27]. This innovative model not only outperformed previous state-of-the-art models but was also reviewed positively by industry practitioners.

Code understanding models such as CodeT5 [83] have enabled further improvements in the quality of generated fixes. As a precursor to modern LLMs like GPT-4 and Llama 3, the CodeT5 architecture allowed researchers to improve the total repair rate for software vulnerabilities. The proposed framework, VulRepair, outperforms VRepair on several metrics due to extensive pre-training and the usage of Byte-Pair Encoding [25].

Recent efforts aim to integrate multiple aspects of automatic programming to enhance effectiveness. Zhou et al. [84] proposed CREAM, an automatic programming framework that leverages LLMs to integrate code search, code generation, and program repair. The framework retrieves similar code snippets through various code search strategies to guide the LLM's code generation process. It validates generated code using compilers and test cases, constructing repair prompts to query LLMs for correct patches. Preliminary experiments showed that CREAM helped CodeLlama solve 267 programming problems with a 62.53% improvement, demonstrating the potential of combining these three research areas.

Understanding why LLMs fail in code generation is crucial. Wen *et al.* [85] analyzed 12,837 code generation errors across 14 LLMs, identifying 19 distinct error causes. They proposed *LlmFix*, a method that addresses three directly fixable error causes through

a three-step process: correcting indentation, truncating redundant code, and importing missing modules. This approach significantly improved LLM performance on the HumanEval and MBPP datasets by 9.5% and 5.4%, respectively, highlighting the importance of automated error correction in enhancing code generation effectiveness.

3.2 LLM-Driven Code Generation

The popularization of LLMs has catalyzed significant interest in their use across various fields. Specifically, the success of automated code generation has been greatly accelerated by improvements in the logical reasoning abilities of these models [86]. State-of-the-art models like GPT-4 [35] have revolutionized code synthesis compared to their predecessors such as CodeBERT [87].

Specialized LLMs for code synthesis have emerged, including CodeX [88], Code Llama [37], Wizard-Coder [89], and CodeGen [90]. Many of these models are trained on publicly available software repositories, enhancing their code generation abilities. For example, CodeGen employs a multi-point synthesis scheme where the user is periodically prompted for feedback on the generated code [90]. However, this method requires active human intervention, as opposed to the fully automated feedback loop provided by *LLM4CVE*.

Despite advancements, LLM-generated code often fails to pass test cases and requires human intervention. Prior efforts often neglected understanding why LLMs failed. Nguyen *et al.* [91] identified various

error causes in LLM-generated code and showcased that directly addressing specific error types can significantly enhance the performance of multiple LLMs without modifying the models themselves.

Frameworks integrating testing and repair mechanisms have been proposed to improve code correctness. AutoSafeCoder, introduced by Nunez et al. [92], is a multi-agent framework that leverages LLM-driven agents for code generation, vulnerability analysis, and security enhancement through continuous collaboration. It consists of a Coding Agent, Static Analyzer Agent, and Fuzzing Agent, integrating dynamic and static testing iteratively during code generation to improve security. Experiments demonstrated a 13% reduction in code vulnerabilities without compromising functionality.

3.3 LLM-Guided Vulnerability Detection and Repair

LLMs have been identified as key components for automatically rectifying software vulnerabilities. This is motivated by the ability of modern LLMs to generate consistently viable code snippets for many common programming languages [93]. Even for programming languages with relatively little toolchain support, augmented LLMs perform remarkably well [94].

A significant amount of literature exists regarding the use of LLMs for automated program repair [95, 96, 97, 98, 99, 100, 101]. Moreover, it has been demonstrated that LLM-based vulnerability repair pipelines can improve end-to-end repair rates [102, 55, 103, 104, 105].

One of the first works on this subject involves using zero-shot prompting to fix security vulnerabilities in a synthetic dataset [103]. Since this work is from 2021, the LLMs used (Codex and Jurassic J-1) are relatively outdated. However, the performance of these techniques is already impressive, with a significant portion of simple, synthetic bugs fixed through the authors' pipeline.

Using the Codex and GPT-3 LLMs, researchers were able to repair 76.8% of bugs in Java programs detected with static analysis tools [98]. Notably, these bugs were often security-related, falling into categories such as Null Pointer Dereferences and

Thread Safety Violations. However, this tool is limited to the C# and Java programming languages, whereas a majority of critical system software is written in languages such as C and C++[106, 107].

There is an existing precedent for providing feedback in the LLM-driven code repair process. Existing implementations often require extensive test suites [55], which are not always available for real-world software. When given representative test cases, these frameworks can repair the majority of bugs automatically.

Nguyen et al. [91] proposed a novel framework that enhances the capability of LLMs to learn and utilize semantic and syntactic relationships from source code data for software vulnerability detection. Their SAFE approach demonstrated superiority over state-of-the-art baselines on real-world datasets (ReVeal, D2A, Devign), achieving higher performances in F1-measure and Recall.

Researchers have also incorporated advanced LLM augmentation techniques such as Low-Rank Adaptations (LoRAs) to fine-tune their code repair models [96]. These methods are similar to our proposed *LLM4CVE* pipeline and have shown significant improvements over non-augmented baselines. The datasets used in this work cover a wide variety of bugs present in everyday software rather than focusing specifically on security vulnerabilities. In comparison, we fine-tune our models on a dataset of real-world security vulnerabilities, as demonstrated in Section 5.1.

4 Methodology

LLM4CVE is an iterative pipeline that intends to automatically rectify common software vulnerabilities through the use of augmented Large Language Models. In this section, we aim to describe the structural and theoretical motivations behind the implementation of the pipeline. A visualization of the LLM4CVE pipeline is given in Figure 4.

4.1 CVE Selection

We select eight of the most common CWEs for our analysis. A brief description of these CWEs along with their relative frequency in our dataset is provided in Table 1. Details on the filtration of vulnerability examples for our pipeline are provided in Section 5.2.

4.2 Prompting

We employ both zero-shot and one-shot prompting for generating code snippets from an LLM. In one-shot prompting, guidance is provided to the model over multiple rounds of code iteration, and the LLM is then able to incorporate feedback into the final code. On the other hand, in zero-shot prompting, no contextual guidance is provided to the model. Therefore, the LLM generates a code snippet without guidance or feedback. All LLMs in our study are tested with both types of prompting.

4.3 Prompt Engineering

The LLM4CVE pipeline employs two types of prompts, classified as "guided" and "unguided", respectively. The "guided" prompt provides the name of the CVE and CWE, a description of both, and specific instructions to further facilitate valid repair. The "unguided" prompt only instructs the model to repair the code – no vulnerability details are provided. We also require the LLM to output code surrounded by delimiters to further optimize the extraction of code from the model output. Moreover, we instruct the model to create compilable code, use proper syntax and make the minimal amount of changes required to fix the target bug, as well as requiring it to synthesize all modifications itself without asking for user input.

Importantly, while CVE descriptions often provide a specific reference to a problem component in a function, CWE descriptions instead categorize the issue into a broad set of vulnerabilities. As a result, the "guided" prompt offers a more thorough description of the problem, which we posit allows for the LLM to generate superior candidate patches.

4.4 Code Analysis

To enable the automated evaluation of the LLM code output, an automated metric is required. For this purpose, we choose CodeBLEU, a widely accepted method for calculating the semantic similarity of two pieces of code [108]. Like its predecessor BLEU [109], which is often used for determining the quality of machine-translated text, CodeBLEU allows us to determine how similar the ground truth fixed code is to the LLM-generated fix. This tool provides scores in the range of 0-100 (we use an implementation that scales these values to 0-1), with a higher score implying the candidate code snippet is similar to the reference snippet. CodeBLEU incorporates the n-gram match from BLEU, in addition to in-depth analysis of code semantics via Dataflow Graphs and Abstract Syntax Trees.

4.5 Iterated LLM Generation

One of the most important parts of the LLM4CVE pipeline is the automated feedback loop between analysis tools and the LLM. This allows for the LLM to generate improved code over multiple iterations, greatly increasing the quality of the final output. To implement this mechanism, we have used the difference in CodeBLEU scores between the broken input code and the LLM-generated output code.

The feedback provided conforms to two guiding principles – (1) the output code should not be dramatically different than the input code, and (2) the output code should be valid C code. Our use of Code-BLEU scoring helps the model achieve both goals, as we can safeguard against excessive semantic changes to the code. Any faults found will automatically trigger another iteration of our pipeline. Then, if any new faults are found in the generated code (perhaps due to a failure of the model to synthesize a valid snippet), this process will be repeated. Ultimately, we collect output from both of these stages, along with the previously generated code and feed it into the LLM in the same context session for each iteration. We impose a limit of two iterations on the pipeline and select the second output as the candidate patch for evaluation.

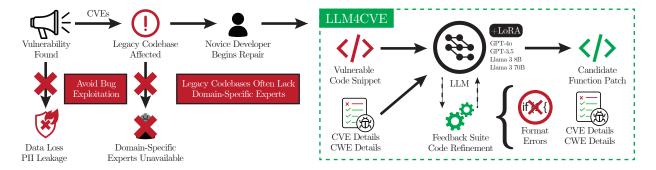


Figure 4: A visualization of how the LLM4CVE pipeline can automatically fix common software vulnerabilities

4.6 Evaluation Process

Unlike many other approaches to automated vulnerability repair with Large Language Models, LLM4CVE targets real-world bugs instead of synthetic vulnerabilities. As a result, the evaluation of code correctness is a significantly more complicated problem. Many vulnerable code snippets are not selfcontained, which means that external context is required to improve generation performance. We tailor of evaluation suite with this fact in mind, focusing on metrics highlighting improvements in code quality, and comparing the semantic similarity of our candidate patches to real-world ground truth solutions. In addition, we perform a selection of end-to-end compilation steps using our generated patches to confirm the viability of our pipeline. We believe this methodology offers a balance between theoretical evaluation and real-world applicability.

Importantly, we note that the nature of extracting function-level vulnerabilities from real-world code-bases implies that these snippets are not fully self-contained. Therefore, it is infeasible to perform traditional static analysis, which necessitates our use of alternative techniques to generate feedback for the iterate steps of our pipeline.

There are multiple valid methods in which to fix a bug. For critical code, it is often more important for a vulnerability to be fixed immediately – even if functionality is impacted. Therefore, a priority in our evaluation scheme is measuring the ability of our pipeline to fix the provided vulnerability. There are scenarios where the ground truth patch differs from our candidate patch, but we are concerned foremost with whether or not the bug is resolved. Then, both patches in this scenario would pass our evaluation method.

5 Experimental Setup

In this section, we discuss the design of our experimental apparatus and provide details on the preprocessing, testing, and evaluation schemes of our work. It is important to note that we use multiple compute nodes equipped with one Nvidia A100, 48 CPU cores, and 256GB of system memory throughout our study.

5.1 Datasets

Our primary dataset of interest is CVEFixes—a repository containing metadata, commit history, CVE/CWE classification, and most importantly: a before-and-after representation of vulnerable code [110]. This dataset contains over 10,000 vulnerable functions, a majority of which have labeled pairs of vulnerable (before) and non-vulnerable (after) code snippets. We use the provided SQL database to extract these labeled pairs, and we further filter them by language. We target the C programming language for the extraction of vulnerable code snippets.

5.2 Dataset Preparation

As provided, the CVEFixes dataset does not lend itself to easy extraction of candidate before-and-after pairs corresponding to each CVE. Therefore, we implement a preprocessing pipeline to extract this information from the dataset. First, we obtain all function-level changes for the target programming languages ordered by CVE and function name, excluding CVEs with an associated CWE with minimal information such as "NVD-CWE-noinfo" and "NVD-CWE-other". We then filter out all CVE+name pairs that do not match our desired pattern of one vulnerable "before" code snippet, and one non-vulnerable "after" code snippet.

After obtaining a feasible set of before-and-after code snippets, we further trim these candidates by removing all pairs where at least one of the code snippets has a token count greater than 500. This ensures that we are not at risk of exceeding the context length of the Large Language Models used in our testing. After our dataset filtration stage, we are left with eight CWEs with at least 100 candidate pairs, representing 697 unique CVEs.

5.3 Large Language Models

For this study, we target the following Large Language Models: GPT-3.5, GPT-40, Llama 3 8B, and Llama 3 70B. Notably, these models represent state-of-the-art performance in the categories of closed-source and open-source models. Importantly, the open-source nature of the Llama 3 family of LLMs enables the training of LoRAs to boost model performance, as explained in Section 5.4. The range in parameter counts also offers an opportunity to explore the performance gradient between the selected models. It is also important to note that GPT-40 is a multimodal LLM, although our pipeline uses only text-based input.

Our selection of LLMs is also motivated by the maximum context length supported by each model. A longer context length enables the LLM to incorporate more information during the generation process, which is especially important during iterative generation, as each iteration builds on top of the existing

context. Therefore, a sufficiently large context window is required for our pipeline to function, which is provided by all tested LLMs. This value was derived from the OpenAI documentation for GPT models [111] and the implementation specifications for the Llama 3 [36] models. Note that the GPT-3.5-Turbo and GPT-40 models available from OpenAI represent the GPT-3.5 and GPT-40 models in our study. A description of the context length and parameter count for each model is provided in Table 2.

Table 2: Context lengths and parameter counts of selected Large Language Models

Model	Context Length (Tokens)	Parameter Count
GPT-3.5	16,385	175B
GPT-4o	128,000	і 1760В [<mark>64</mark>]
Llama 3 8B	8,192	8B
Llama 3 70B	8,192	70B

5.4 LLM Augmentation

We train a Low-Rank Adaptation on the Llama 3 70B LLM using a portion of our created dataset. We employ an 90/10 train/test split to ensure sufficient data is available for our evaluation. We train on labeled "broken"/"fixed" pairs, corresponding to the pre-fix and post-fix ground truth data. Then, we evaluate the LLM+LoRA on the test set by requesting for the set of broken code samples to be rectified. A complete description of our evaluation metrics is provided in Section 5.8.

5.5 Pipeline Configurations

We use three pipeline configurations – (1) "unguided", (2) "guided", and (3) "guided+feedback". The third configuration also includes the trained LoRA for the Llama 3 70B model. An explanation of the prompting scheme and the feedback mechanism is shown in Section 4.3 and Section 4.5, respectively. Across our five tested models, this results in 15 potential model/configuration combinations. Note that we use a random sample consisting of 50% of the full dataset for the "guided+feedback" configuration.

We provide a full model/configuration diagram in Table 3.

Table 3: Models & pipeline configurations used in our study

Model	"unguided"	"guided"	"guided+feedback"
GPT-3.5	✓	✓	✓
GPT-4o	✓	✓	✓
Llama 3 8B	✓	✓	✓
Llama 3 70B	✓	✓	✓

5.6 Automated Pipeline Feedback

The LLM4CVE pipeline employs a "guided with feedback" approach that combines prompt engineering and iterative generation to produce higher-quality vulnerability patches, limited to two iterations for performance and computational efficiency.

To avoid exceeding the LLM's context window and prevent catastrophic forgetting, each prompt and vulnerable code snippet is kept around 500 tokens. Feedback prompts are similarly sized because they include the in-progress code at each iteration step.

After obtaining output from the LLM, and if we have not reached our iteration limit as defined in Section 4.5, we extract the code and submit it for testing. We analyze the change in CodeBLEU score between the current and previous code versions, as explained in Section 4.4, to identify issues. If the CodeBLEU score diverges significantly, it likely indicates an error, and we inform the LLM that the candidate patch may be incorrect in the next prompt. Importantly, we never compare the CodeBLEU score of the candidate patch to the ground truth, as our pipeline would not have access to the ground truth fix in real-world use.

A complete description of our pipeline's iterative generation step is provided in Figure 5.

5.7 Candidate Patch Extraction

After obtaining an output from the LLM, we must extract only the code from it, discarding any delimiters or extraneous commentary. From our analysis, approximately 95% of responses are well-formed,

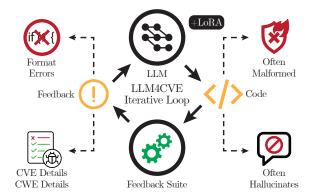


Figure 5: LLM4CVE uses iterative generation to improve the overall quality of patch synthesis

following the code block formatting specified in the prompt. For these responses, we simply extract the candidate patch from the code block. The remaining responses require nontrivial logic to extract patches from, which we implement as well. In the case where we detect no code has been generated (†1% of samples), we output no candidate patch instead.

5.8 Metrics

We use four principal metrics for evaluation – Code-BLEU scores, human quality evaluation, end-to-end compilation, and required engineering effort. We employ a pass @ k scheme, with k=1, as described in [88]. Detailed descriptions of our chosen metrics are provided below.

5.8.1 CodeBLEU Scores

We evaluate the final output code from all configurations and model types against the ground truth non-vulnerable code snippet. As a higher CodeBLEU score implies greater semantic similarity between two pieces of code, a large (i.e. near 1.00) score between the ground truth and the output code implies greater potential for valid bug correction. Importantly, a candidate patch with a CodeBLEU score less than 1.0 can still be a viable fix, as there are often multiple solutions to the given vulnerability.

5.8.2 Human Quality Scores

This metric provides a measure of the functionality and reliability of the proposed patch. A high score in this category implies that the generated fix is likely to be high-quality, usable code. Moreover, the demonstration of greater confidence in the proposed patch by the human reviewers also validates the practical applicability of our pipeline.

5.8.3 End-to-End Compilation

Next, we test our pipeline's generated patches in real-world codebases. We directly apply the result of our pipeline to the codebase affected by the vulnerability. Then, we compile the entire project and determine the validity of the fix. This metric measures the ability for the LLM4CVE pipeline to fix real-world security vulnerabilities. It also ensures that the pipeline output is compliant, compiliable code.

5.8.4 Engineering Effort

Finally, we analyze the engineering effort required between traditional approaches and our pipeline. We compare setup times, the level of experience required, and the technical complexity of the proposed technique.

6 Results

In this section, we present the results of our evaluation of the LLM4CVE pipeline. We measure four key metrics – CodeBLEU Scores, Human Quality Scores, End-to-End Compilation success rate, and required Engineering Effort. These metrics enable a multifaceted assessment of the practicality, functionality, and effectiveness of the LLM4CVE pipeline. We provide visual comparisons between the various configuration of our pipeline over the five Large Language Models described in Section 5.3. Moreover, we compare pipeline results between all three configurations across the eight CVEs used.

6.1 CodeBLEU Scores

For this metric, we compare the CodeBLEU scores between the pipeline output and the ground truth fix. Our CodeBLEU software tool generates semantic similarity ratings in the range of 0.0-1.0. A score of 1.0 implies an exact match when considering ngrams, syntax, and dataflow between the two samples. An important consideration to keep in mind is that there may be multiple "valid" fixes for a CVE, so an inexact match is not necessarily indicative of invalid code. Therefore, we treat this metric as a probabilistic estimate of the likelihood of generating a viable candidate fix. We extend this evaluation with real-world evaluation of selected candidate patches in Section 6.3.

We include results for all three pipeline configurations – "unguided" (zero-shot), "guided" (one-shot), and "guided+feedback" (one-shot with feedback) – and the semantic similarity scores are presented in Figure 6. Importantly, the full configuration of the LLM4CVE pipeline – "guided+feedback" – demonstrates a remarkable performance improvement across all models, with the Llama 3 70B LLM peaking at a 20% increase in semantic similarity scores.

6.2 Human Quality Scores

We perform a human study² over a group of participants with at least several years of experience in programming. Our metrics are centered around functionality evaluations. Participants understood the purpose of the study – including the presence of one ground-truth patch and two LLM-generated patches per example – but were not told which LLM created each candidate patch. In total, we include selected outputs from the Llama 3 70B and GPT-40 models. We include the output of the "guided+feedback" configuration for each model, along with the ground truth fixed code snippet, for three total candidate patches per function.

For each function, we showed participants the

²We received prior approval to conduct this study from an institutional IRB through an exemption due to the strictly academic nature of our questionnaire.

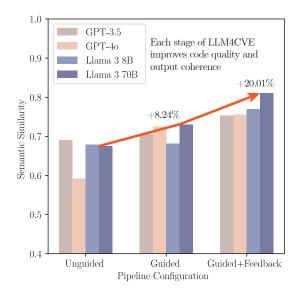


Figure 6: Semantic similarity scores across all pipeline configurations and model types

CWE name, CWE description, CVE name, and CVE description for the vulnerability in question. Then, we asked them the following questions:

- Vulnerability Elimination: On a scale of 1-10, how accurately does the following code eliminate the security vulnerabilities mentioned above?
- Code Style: On scale of 1-10, how well does the following code adhere to best practices for code style?

Note that we compare and normalize the results of the first question with the known correctness of the ground-truth score in mind. We also observe that a majority of correctness ratings are centered around 1 (completely incorrect), or 10 (completely correct). Performing a qualitative evaluation of the LLM4CVE pipeline highlights its strengths in a real-world setting. Moreover, this approach allows for a multifaceted assessment of the usefulness and practicality of our LLM-based vulnerability repair model by industry practitioners. We present the results of the human study in Table 4.

Table 4: Human evaluation of the LLM4CVE pipeline

Patch Source	Configuration	Style	Correctness
GPT-4o	"guided+feedback"	9.01	7.44
Llama 3 70B	"guided+feedback"	7.81	8.51
Ground Truth	×	4.24	10.00

6.3 End-to-End Compilation

For this test, we focus on evaluating the pipeline's effectiveness in fixing real-world bugs. We begin by initializing our pipeline with a vulnerable function and associated prompt. As an example, the cJSON_DeleteItemFromArray function from the iperf3 tool is chosen. This tool is a TCP, UDP, and SCTP network bandwidth measurement tool, and uses the library cJSON, in which this vulnerability lies. The software is affected by CVE-2016-4303 (CWE-120).

Once a candidate patch is obtained, we move to evaluation of its viability. We create a testing harness that exploits the vulnerability at hands and compile the program with and without the candidate patch. Our harness poses as a malicious actor trying to crash the software by providing a malformed cJSON object with invalid lengths. Then, we run both programs and note which program crashes. Through this evaluation, it was confirmed that the candidate patch prevented the malicious actor from exploiting this vulnerability by rejecting the malformed object, demonstrating the effectiveness of the LLM4CVE pipeline. We provide further details of our testing harness in our public release of the pipeline, which can be found in Section 9.

6.4 Engineering Effort

Software solutions must be evaluated for efficiency and real-world practicality. We compare the ease of use and complexity of traditional human repair, GPT-based solutions, and open-source LLMs. Human repair costs are estimated from published data, while other statistics come directly from our pipeline.

GPT models are relatively efficient to set up due to OpenAI's simple API for inference, requiring no user compute resources. Open-source LLMs offer data security by allowing on-site training and inference but require significantly more setup time and manual configuration; their speed depends on access to GPU resources.

Trained engineers are the slowest method, as skilled human labor is needed to fix security vulnerabilities. In legacy codebases, this issue is worsened due to inaccessible or missing expertise. Studies estimate that human engineers take between several days [112] and one month [110] to repair a security vulnerability. We combine setup and execution time into one statistic for this category.

Time values for LLMs are based on our team's average time to set up a basic GPT/Llama pipeline and produce a single candidate patch. The LoRA training process requires access to relevant datasets like CVE-Fixes, and we include an estimate of training time in our evaluation. A comparison of the average time costs among these approaches is given in Table 5.

Table 5: Comparison of engineer-hours required for selected vulnerability patching techniques

Technique	Setup Time	Execution Time
Human Intervention	×	28 days [110]
Open-Source LLMs+LoRAs	24 hours	10 minutes
GPT LLMs	1 hour	5 minutes

7 Discussion

Our proposed pipeline lowers the barrier to entry for repairing critical security vulnerabilities, especially in legacy codebases. Significantly less engineering effort is required in these types of projects with deteriorating knowledge bases and few active maintainers. Moreover, the speed and efficiency of our pipeline enable these fixes to be made with haste, lessening the time between the discovery of a bug and its associated patch.

7.1 Impact

The LLM4CVE pipeline enables the quick repair of ⁷₈ vulnerabilities in critical system software. Moreover, ⁹

our tool is of increased relevance to legacy codebases, where devoted maintainers are often in short supply, and turnaround times are often long. By lessening the dependence on these domain-specific experts, our pipeline enables critical security vulnerabilities to be patched faster, increasing the overall safety of these programs.

These benefits are further enhanced by the speed of our pipeline, as demonstrated in Table 5. Applying patches in time-sensitive environments – such as when a new vulnerability is discovered – is desirable to maintain system integrity and robustness.

7.2 Candidate Patch Assessment

It is of interest to compare a patch generated by the LLM4CVE pipeline to the original vulnerable function. We provide a candidate patch for the snmp_ber_decode_type function affected by CWE-125 and CVE-2020-12141. Below, Listing 1 is the original vulnerable code, while Listing 2 is generated by GPT-40 using our fully-featured pipeline.

```
unsigned char * snmp_ber_decode_type(
    unsigned char *buff, uint32_t *buff_len,
    uint8_t *type)
{
    if(*buff_len == 0) {
        return NULL;
    }

    *type = *buff++;
    (*buff_len)--;
    return buff;
}
```

Listing 1: The original vulnerable function

10 }

Listing 2: A candidate patch generated by GPT-40

We see that the LLM output checks the validity of the input variables buff, buff_len, and type, while the vulnerable code only attempts to validate buff_len (and that too with a blind dereference). Then, it is evident that our pipeline was able to patch the vulnerability in a viable, non-destructive manner.

7.3 GPT vs. Llama

Throughout our experiments, the Llama 3 70B model consistently matched or outperformed other LLMs. especially using the full LLM4CVE pipeline. Even the relatively smaller Llama 3 8B model can compete with the GPT models once fine-tuning is performed. This demonstrates the effectiveness of Parameter-Efficient Fine-Tuning techniques like LoRAs, as without these adapters the GPT and Llama models perform roughly equivalently in the "guided" (one-shot) pipeline configuration. The largest gains in generation ability were derived from the iterative configuration of our pipeline, and this can be attributed to our fine-tuning of open-source models. Some LLMs such as GPT-40 are not fine-tunable, and so we are unable to apply all techniques mentioned in Section 4 to these models.

7.4 Ethical Considerations

Our tool serves to rectify vulnerabilities in codebases where the maintainers would otherwise be unable to do so themselves. As a result, we expect that: (1) public usage of our tool will serve the security community by keeping the end-user better protected from cybercriminals, and (2) there are no significant ethical risks posed by our pipeline. In addition, all vulnerabilities studied were already publicly disclosed by nature of being a known CVE. Therefore, no further vulnerability disclosure is necessary.

8 Conclusion

The LLM4CVE pipeline serves to fix security vulnerabilities in critical system software with minimal

human input. By combining traditional bug repair methods with state-of-the-art Large Language Model techniques, we improve the robustness and viability of automated program repair. Our iterative pipeline allows for gradual refinement of the generated code, which increases the likelihood of obtaining a viable candidate patch. We further extend LLM4CVE with automated code analysis tools, LLM fine-tuning, and Prompt Engineering. A thorough evaluation of real-world vulnerabilities through both automated and human-centered means has shown the efficacy of our approach, and we believe our contributions to the field will pave the way towards achieving automated program repair without any intervention from trained experts.

9 Code Availability

We publish our testing apparatus, fine-tuned weights, and experimental data on our website³.

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³https://sites.google.com/view/llm4cve

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