# LLM4Vuln: A Unified Evaluation Framework for Decoupling and Enhancing LLMs' Vulnerability Reasoning

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#### **Abstract**

Large language models (LLMs) have demonstrated significant potential in various tasks, including vulnerability detection. However, current efforts in this area are preliminary, lacking clarity on whether LLMs' vulnerability reasoning capabilities stem from the models themselves or external aids such as knowledge retrieval and tooling support.

This paper aims to isolate LLMs' vulnerability reasoning from other capabilities, such as vulnerability knowledge adoption, context information retrieval, and structured output generation. We introduce LLM4Vuln, a unified evaluation framework that separates and assesses LLMs' vulnerability reasoning capabilities and examines improvements when combined with other enhancements.

We conducted controlled experiments with 97 ground-truth vulnerabilities and 97 non-vulnerable cases in Solidity and Java, testing them in a total of 9,312 scenarios across four LLMs (GPT-4, GPT-3.5, Mixtral, and Llama 3). Our findings reveal the varying impacts of knowledge enhancement, context supplementation, prompt schemes, and models. Additionally, we identified 14 zero-day vulnerabilities in four pilot bug bounty programs, resulting in \$3,576 in bounties.

#### 1 Introduction

In the rapidly evolving landscape of computer security, Large Language Models (LLMs) have significantly transformed our approach to complex challenges. Distinguished by extensive pre-training and strong instruction following capabilities, these models excel in understanding and interpreting the semantics of both human and programming languages. This has led to the emergence of *LLM-based vulnerability detection*, offering superior intelligence and flexibility compared to traditional program analysis-based vulnerability detection

(e.g., [15, 16, 28, 29, 55, 63, 65, 68]) and neural network-based vulnerability detection (e.g., [17, 20, 44, 54, 67, 72]).

Under this emerging paradigm, triggered by the successful release of ChatGPT [13, 38, 48] on November 30, 2022, related research primarily focuses on two dimensions. One dimension involves designing *specific LLM-based detectors* for different security problems. For example, researchers have developed TitanFuzz [24], FuzzGPT [25], Fuzz4All [66], and ChatAFL [47] for fuzzing various vulnerabilities; GPTScan [56] and GPTLens [33] for detecting smart contract vulnerabilities; and LLift [42] and LATTE [46] for LLM-enhanced program and binary analysis.

The other dimension aims to *benchmark or evaluate* LLMs' capabilities in vulnerability detection. It examines how different models, configurations, and instructions influence detection results, addressing the key question, "How far have we come?" in LLM-based vulnerability detection. Notably, Thapa *et al.* [58] pioneered this effort by benchmarking transformer-based language models against RNN-based models for software vulnerability detection. Following the release of ChatGPT and GPT-4, additional LLM-focused benchmark studies have been conducted, including for smart contracts [18,23], traditional C/C++/Java vulnerabilities [26,31,37,60], and vulnerability repair [50,69].

Our research falls into the second dimension. However, instead of focusing on the performance of individual LLM instances and their configurations, we delve into the paradigm itself and consider what is missing or could be improved. To this end, we first abstract and generalize the paradigm of LLM-based vulnerability detection into an architecture shown in Figure 1. Existing LLM-based vulnerability detection typically takes a piece of target code (TC) and asks the LLM to determine whether TC is vulnerable under certain prompt schemes (e.g., role playing [33] and chain-of-thought [64]). However, the additional information about TC (e.g., the context of functions and variables involved in TC), which can be obtained by LLMs through invoking tool support, is often overlooked in the paradigm.

More importantly, LLMs are pre-trained up to a certain

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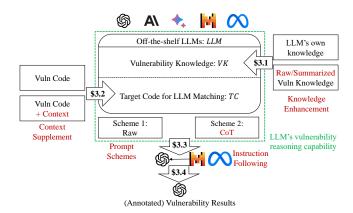


Figure 1: An illustration of the LLM-based vulnerability detection paradigm and the LLM4Vuln framework.

cutoff date<sup>1</sup>, making it challenging for LLMs to adapt to the latest vulnerability knowledge. In other words, it is essential to incorporate relevant vulnerability knowledge (VK) into the paradigm. Furthermore, open-source LLMs typically have weaker instruction-following capabilities than OpenAI models, due to the latter being aligned with extensive reinforcement learning from human feedback (RLHF) [40], which could indirectly affect the LLM's reasoning outcome in automatic evaluation. As we can see from above, the LLM's vulnerability reasoning capability can be influenced by various factors beyond the model itself and its configuration.

Based on this intuition, rather than treating LLM-based vulnerability detection as a whole for evaluation, we *decouple* LLMs' vulnerability reasoning capability from their other capabilities *for the first time* and assess how LLMs' vulnerability reasoning could be enhanced when combined with the enhancement of other capabilities. As for benchmarking and tuning the model itself under different configurations (e.g., different temperatures), we defer to another dimension of related work focused on how to pre-train vulnerability-specific or security-oriented LLMs [19,27,30,32,35,39,43,49,51,62,73], which goes beyond merely being a language model.

To achieve this research objective, we propose LLM4Vuln, a unified evaluation framework for decoupling and enhancing LLMs' vulnerability reasoning. As illustrated in Figure 1, LLM4Vuln first considers the state-of-the-art LLMs' ability to actively invoke tools for seeking additional information about TC, such as through function calling in proprietary OpenAI models [9] and in fine-tuned open-source models [10,11]. Besides supplying additional information for TC through LLM-invoked tools, LLM4Vuln also decouples and enhances LLMs' VK by providing a searchable vector database of vulnerability knowledge, similar to retrieval-augmented generation (RAG) [41] technique for NLP-domain knowledge enhancement. Furthermore, LLM4Vuln incorporates typi-

cal prompt engineering enhancements by exploring different prompt schemes and employs the most capable GPT-4 model to refine the raw, unstructured output of models with less proficient instruction-following capabilities. More specifically, LLM4Vuln introduces the following design:

- For knowledge enhancement, LLM4Vuln not only incorporates raw vulnerability reports for knowledge retrieval but also considers summarized vulnerability knowledge. However, the summarized knowledge cannot be directly searched using only TC. Hence, during the automatic summarization of vulnerability knowledge, we also generate descriptions of the functionality or applicable scenarios for each original vulnerability. By embedding these summarized functionalities into a vector database, we enable the retrieval of relevant VK based on the similarity between its corresponding functionality and that of TC.
- For *context supplementation*, we provide LLMs with the context of *TC* through external program analysis to ensure a fair comparison among different models. In real-world vulnerability detection, LLMs can obtain context information through the function calling mechanism [9].
- For *prompt schemes*, we adopt common practices such as chain-of-thoughts (CoT) [64]) and customize it into two specific CoT schemes for vulnerability analysis. The details will be introduced in §3.3.
- For instruction following, we use a well-instructed model to align and structure the analysis output of a lessinstructed model, facilitating automatic result evaluation.

In this paper, we focus on the implementation of LLM4Vuln on Solidity and Java, which are popular programming languages for smart contracts and traditional software, respectively. Bug types in Solidity and Java are significantly different, as is the associated knowledge. To address this, we have built a knowledge database consisting of 1,013 high-risk vulnerability reports for Solidity smart contracts and 77 Common Weakness Enumeration (CWE) vulnerability categories for Java to enhance knowledge. Additionally, we collected 51 vulnerable code segments for Solidity and 47 for Java, as well as an equal number of non-vulnerable code segments, for evaluation with ground-truth.

By testing these 194 pieces of code across 9,312 scenarios, which include three types of knowledge enhancement (one with only LLMs' pre-trained knowledge), two context supplementation options (with or without context supplementation), and two prompt schemes (raw and CoT), and using four representative LLMs (GPT-4, GPT-3.5, Mixtral, and Llama 3), we identify the following four findings (more details in §5) based on the benchmark results annotated by LLMs in §3.4):

 (Knowledge Enhancement) Knowledge enhancement has diverse impacts across different programming languages.

<sup>&</sup>lt;sup>1</sup>For example, gpt-4-1106-preview was pre-trained using data up to April 2023, while Code Llama was trained with data up to July 2023; see §2.

Positive impacts are observed in languages (e.g., Solidity) with more logic vulnerabilities, while negative impacts may occur in traditional languages (e.g., Java) that have well-organized CWE categories. Regardless of the language, summarized knowledge improves LLMs' vulnerability reasoning more effectively than original vulnerability reports.

- (Context Supplementation) Supplying context may not always enhance LLMs' ability to reason about vulnerabilities. It may also lead to distractions, hindering LLMs from accurately identifying vulnerabilities.
- (Prompt Schemes) Chain-of-thought based prompt schemes significantly affect LLMs' performance in vulnerability detection. Decomposing complex tasks into simpler sub-tasks helps improve LLMs' performance.
- (Model Selection) The enhancement discussed in this paper has a similar impact on the performance of different models. However, for models with poor capability in vulnerability detection, the impact of these factors is less significant.

Besides findings on benchmarking LLMs' vulnerability reasoning, we also conducted a pilot study in §5.5 on using LLM4Vuln to test four real-world projects in crowdsourcing audit bounty programs. We submitted a total of 29 issues to these four projects, respectively, and 14 of these issues were confirmed by the project teams, leading to \$3,576 in bug bounty being awarded. The discovery of these 14 zero-day vulnerabilities demonstrates the practical impact and value of LLM4Vuln. We further conducted a case study on four publicly available vulnerabilities, which shows that LLM4Vuln can effectively detect vulnerabilities missed by existing tools, even when these vulnerabilities do not exactly match the knowledge in the vector database of LLM4Vuln.

#### 2 Background

Generative Pre-training Transformer (GPT) models, exemplified by the pioneering GPT-3 [48], represent a class of extensive language models trained on diverse text corpora covering a wide range of knowledge across various domains. As indicated in Table 1, there are different variants of such Large Language Models (LLMs), including the GPT series from OpenAI, such as GPT-3.5-turbo, GPT-4, and GPT-4-turbo. There are also open-source implementations, like Mixtral [12, 34] and Llama 2/3 [59]. Mixtral, developed by Mistral AI, matches or outperforms the Llama 2 family and surpasses GPT-3.5 in most benchmarks. Mixtral-8x7b-instruct is a fine-tuned version of mixtral-8x7b, optimized for instruction following. Llama 3, a more recent and powerful model, outperforms GPT-4-turbo in some benchmarks. Code Llama-13B [6, 52] from Meta AI is trained on 13 billion tokens of

Table 1: Major LLMs used for security tasks (input price and output price are in USD per 1M tokens).

Model API	Max.	Knowledge	Input	Output
Model API	Token	Cutoff Date	Price	Price
gpt-4-1106-preview	128k	04/2023	10	30
gpt-4-32k-0613	32k	09/2021	60	120
gpt-4-0613	8k	09/2021	30	60
gpt-3.5-turbo-1106	16k	09/2021	1	2
mixtral-8x7b	32k	Summer 2023	0.30	1
mixtral-7b	32k	Summer 2023	0.05	0.25
llama-3-8b	8k	03/2023	0.05	0.25
codellama-13b	16k	07/2023	0.1	0.5

code and comments from GitHub, employing a learning system known as spaced repetition to focus training on tasks where the model is more likely to make errors.

These models can be tailored for specific applications using methods like fine-tuning or zero-shot learning, enabling them to utilize tools and address problems beyond their initial training data [38,53]. OpenAI and other research groups have demonstrated the effectiveness of these approaches in preparing LLMs for interactive use with external tools. Moreover, LLMs can engage with knowledge beyond their training datasets through skillful in-context learning prompts, even without fine-tuning [22]. However, not all in-context learning prompts are equally effective for tasks like vulnerability detection. Additionally, Wei et al. introduced the "chain-of-thought" prompting methodology [64], which enhances reasoning by breaking down tasks into sequential steps. This approach prompts LLMs to address each step individually, with each stage's output influencing the next, fostering more logical and coherent outputs.

However, the application of these techniques in vulnerability detection specifically remains an area of uncertainty. It is unclear how these methods could be used to improve precision or recall in LLM-based vulnerability detection. Also, the type of knowledge that could be effectively integrated into in-context learning to boost performance in vulnerability detection tasks needs further investigation and clarification.

#### 3 The LLM4Vuln Framework

In this section, we introduce the design of LLM4Vuln, a modular framework to support the paradigm of LLM-based vulnerability detection. As illustrated in Figure 2, LLM4Vuln supports four types of pluggable components for evaluating and enhancing an LLMs' vulnerability reasoning capability. These components are *Knowledge Retrieval*, *Context supplement*, *Prompt Schemes*, and *Instruction Following*. All components are well-decoupled, allowing for easy replacement with other implementations. For each component of LLM4Vuln, only one implementation is required for it to function effectively.

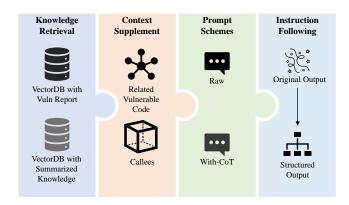


Figure 2: LLM4Vuln's four pluggable components for evaluating and enhancing LLMs' vulnerability reasoning capability.

The first component (§3.1) aims to provide LLMs with up-to-date knowledge of vulnerabilities. In LLM4Vuln, we have designed two types of vector databases for knowledge retrieval: one stores the original vulnerability reports, and the other contains summarized knowledge of vulnerabilities.

The second component (§3.2) provides context supplements to support the vulnerability detection process. In LLM4Vuln, we utilize two types of context supplements: related vulnerable code extracted from the vulnerability reports of the vulnerable samples and the callees for all samples. For a fair evaluation of LLMs across different tests, this part is implemented by static analysis tools for stable contexts, which are processed before feeding the code into LLMs.

The third and fourth components are both discussed in §3.3. The Prompt Schemes component aims to provide enhanced instructions to LLMs to improve reasoning. For this purpose, we design two prompt schemes: *Raw* and *CoT*. Specifically, the Raw prompt scheme simply asks LLMs to reason about a vulnerability without special instructions, while CoT is a chain-of-thought prompt scheme. Besides prompt schemes, LLM4Vuln also aims to enhance instruction-following for structured output, which facilitates the automatic evaluation of results.

Lastly, for benchmarking purposes only, we design an LLM-based result annotation component in §3.4.

## 3.1 Retrieving Vulnerability Knowledge

Although LLMs are trained with extensive code vulnerability data, they typically have a knowledge cutoff date for pretraining, as indicated in Table 1. As a result, LLMs do not have up-to-date vulnerability knowledge, which is particularly crucial for detecting dynamically evolving logic vulnerabilities, such as those found in smart contracts. To address this issue, LLM4Vuln proposes two types of knowledge retrieval methods for enhancing vulnerability knowledge in LLMs, as illustrated in Figure 3.

In the first type, as illustrated in the left part of Figure 3,

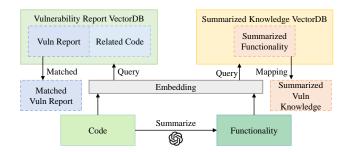


Figure 3: Two types of vulnerability knowledge retrieval.

we collect original vulnerability reports along with the corresponding vulnerable code. We calculate their embeddings and create a vector database containing both the embeddings of the code and the associated vulnerability report. When a target code segment TC is provided, it can be used to directly search the vector database for the most similar code segments. Since a code segment may include both code and comments, the comments can match the vulnerability reports, and the code can correspond to the code mentioned in the report. After the retrieval process, we use only the text of the vulnerability report, excluding the code, as raw vulnerability knowledge for subsequent analysis.

In the second type, we first use GPT-4 to summarize the vulnerability reports. This summary includes the functionality of the vulnerable code and the root cause of the vulnerability, encapsulated in several key sentences. The prompts used for summarizing the code's functionality and the key concept causing the vulnerability, as well as examples of the summarized knowledge, can be found in Appendix A and C, respectively.

With the functionality and knowledge from past vulnerability reports summarized, as depicted in the right part of Figure 3, we then calculate the embedding of this functionality part and create a vector database that contains only the functionality embeddings. When a target code segment TC is provided, we use GPT-4 to first summarize its functionality and then use this extracted functionality to retrieve similar functionalities in the vector database. With the matched functionality, we can directly retrieve the corresponding vulnerability knowledge as *summarized* knowledge for further analysis.

With the vector database, we can provide token-level similarity matching of knowledge to LLMs to enhance their understanding of vulnerabilities. The proposed method can also be easily extended to include other types of knowledge in natural language. For example, it can utilize other graph-based similarity-matching algorithms to match the control flow or data flow of the code segment with the knowledge.

## 3.2 Context Supplementation

As previously illustrated in Figure 2, LLMs may detect vulnerabilities based on the provided code context of the target code *TC*. Sometimes, the trigger of a vulnerability may be hidden in multiple functions or may require additional context to be detected. Even if the triggering logic is entirely within the given code segment, context may help a large language model better understand the function semantics.

In this paper, we provide two types of context supplements: related vulnerable code extracted from the vulnerability reports of the vulnerable samples and the callees for all samples. For the first type, we extract all the functions that are mentioned in the vulnerability reports, such as those from Code4Rena and issues from GitHub. For the second type, we extract all the callees for all the samples, which can be used to provide a better understanding of the code. The context supplements are processed before feeding the code into LLMs. For benchmarking purposes only, we use static analysis to ensure the same contexts for the given code across all models, achieving a fair comparison.

In real-world LLM-based vulnerability detection, LLMs can utilize the function calling mechanism [9, 53] to assist themselves in retrieving extra context information. For example, we can define a series of function calling APIs, such as getFunctionDefinition, getClassInheritance, getVariableDefinition, along with a description of the usage of each function, to assist LLMs in actively calling the function when they require the information. More complicated contexts, such as control and data information, still need to be provided by static analysis tools though.

## 3.3 Prompt Schemes & Instruction Following

In this section, we describe the enhancement of prompt schemes and instruction following.

**Prompt Schemes.** As described in §3.1, there are two types of knowledge provided to LLMs: the original vulnerability reports and the summarized knowledge of vulnerabilities. Additionally, LLMs possess inherent knowledge of vulnerabilities from their training. Therefore, we have designed three prompt schemes corresponding to three types of knowledge usage: *LLM's own knowledge, Raw knowledge*, and *Summarized knowledge*. Figure 4 illustrates how these types of knowledge can be combined with different CoT instructions to form three kinds of prompt schemes:

- In *Scheme 1 Raw*, we simply ask LLMs to generate results without any specific instructions. LLMs can use the APIs mentioned in §3.2 to retrieve related code segments. For open-source models, this scheme does not include this particular sentence.
- In *Scheme 2 CoT*, we request LLMs to follow chainof-thought instructions before generating the result. The

#### Prompt Combination: Knowledge + Output + Scheme

## Knowledge

#### Prefix 1 - LLM's own knowledge:

As a large language model, you have been trained with extensive knowledge of vulnerabilities. Based on this past knowledge, please evaluate whether the given smart contract code is vulnerable.

#### Prefix 2 - Raw knowledge:

Now I provide you with a vulnerability report as follows: {report}. Based on this given vulnerability report, pls evaluate whether the given code is vulnerable.

#### **Prefix 3 - Summarized knowledge:**

Now I provide you with a vulnerability knowledge that {knowl}. Based on this given vulnerability knowledge, evaluate whether the given code is vulnerable.

#### **Output Result:**

In your answer, you should at least include three parts: yes or no, type of vulnerability (answer only one most likely vulnerability type if yes), and the reason for your answer.

#### Scheme 1 - Raw:

Note that if you need more information, please call the corresponding functions.

#### Scheme 2 - CoT:

Note that during your reasoning, you should review the given code step by step and finally determine whether it is vulnerable. For example, you can first summarize the functionality of the given code, then analyze whether there is any error that causes the vulnerability. Lastly, provide me with the result.

Figure 4: Two prompt schemes combined with three different knowledge prefixes, yielding six detailed prompts.

LLMs should first summarize the functionality implemented by the given code segment, then analyze for any errors that could lead to vulnerabilities, and finally determine the vulnerability status.

Improved Instruction Following. Since all outputs from LLMs are in natural language, they are unstructured and need summarization and annotation to derive the final evaluation results. LLMs have been successfully utilized as evaluators [21,45], and we use GPT-4 to automatically annotate the outputs of LLMs. The function calling API is employed to transform unstructured answers into structured results. Specifically, LLM4Vuln generates structured results based on the answers provided by different prompt schemes and LLMs.

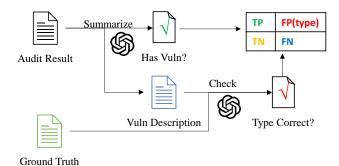


Figure 5: The process of automatic annotation by GPT-4.

These results include two parts: whether the LLM considers the code to be vulnerable, and the rationale for its vulnerability or lack thereof. The specific prompt used for this process can be found in Appendix A. Following this step, we can automatically annotate all the outputs from LLMs.

#### 3.4 LLM-based Result Annotation & Analysis

The components mentioned above are designed to enhance LLMs' vulnerability reasoning capabilities. However, there is also a need for a component that enables automatic evaluation of LLMs' reasoning on vulnerabilities. As such, we have designed LLM4Vuln to perform LLM-based result annotation, which is used to obtain the final evaluation results after individual LLMs generate their raw output.

Based on the raw Yes/No output from individual LLMs and whether the vulnerability type matches, as annotated by GPT-4, LLM4Vuln automatically obtains the following annotation results in terms of true positives, true negatives, false negatives, false positives, and false positive types:

**TP** (**True Positive**): The LLM correctly identifies the vulnerability with the correct type.

**TN** (**True Negative**): The LLM correctly concludes that the code is not vulnerable.

**FN** (**False Negative**): The LLM incorrectly identifies a vulnerable code segment as non-vulnerable.

**FP** (**False Positive**): The LLM incorrectly identifies a non-vulnerable code segment as vulnerable.

**FP-type** (**False Positive Type**): The LLM identifies a vulnerable code segment as vulnerable, but with an incorrect vulnerability type.

Since FP-type includes both false positives (reporting a non-existent vulnerability) and false negatives (failing to report an existing vulnerability), we calculate the precision and recall of the LLMs' vulnerability detection results as follows:

$$Precision = \frac{TP}{TP + FP + FP_{type}}$$

$$TP$$
(1)

$$Recall = \frac{TP}{TP + FN + FP_{type}} \tag{2}$$

Table 2: Datasets used in the evaluation.

Dataset	Samples	Projects	Period
Solidity Knowledge set	1,013	251	Jan 2021 - Jul 2023
Solidity Testing set	51 + 51	11	Aug 2023 - Jan 2024
Java Knowledge Set	77	N/A	N/A
Java Testing Set	46 + 46	N/A	Jan 2013 - Dec 2022

## 4 Implementation and Setup

With LLM4Vuln's modular design introduced in §3, we now target a detailed implementation of LLM4Vuln in this section. In this paper, we focus on LLM4Vuln's application to Java programs and smart contracts written in Solidity [1]. The choice of Java is motivated by its popularity and the availability of a large number of vulnerabilities in the CWE database [8] and CVE database [7]. While smart contracts as the analysis subject targeted in this paper mainly because LLMs have demonstrated greater effectiveness in identifying logic vulnerabilities in natural-language-like Solidity contracts [33, 56] than in detecting traditional vulnerabilities in C/C++ programs [42, 46]. Moreover, compared to traditional memory corruption vulnerabilities, smart contracts are more security-critical and could directly cause huge financial losses if exploited [71]. Nevertheless, while we believe that the design of LLM4Vuln is generic and extendable to other programming languages, the concrete extension may still require considerable effort, and we leave this implementation extension to future work.

#### 4.1 Data Collection and Testing

§3.1 introduced the methodology by which LLM4Vuln builds a vulnerability knowledge base and enables vector-based knowledge retrieval. In this section, we choose two different programming languages, Solidity and Java, to evaluate the effectiveness of LLMs in vulnerability detection. Java is one of the most widely used programming languages and has a large number of vulnerabilities, most of which are related to features of the programming language, such as unsafe deserialization. In contrast, Solidity is an object-oriented programming language for writing smart contracts on the Ethereum blockchain, and most of the vulnerabilities are related to business logic. The collected data have two parts: the first is for building the knowledge database, and the second is for testing the effectiveness of the LLMs.

For Solidity, we collected all the data from Code4Rena [5], a popular crowdsourcing auditing platform for smart contracts. To build the knowledge database, we used all the high-risk vulnerabilities from its GitHub issues [4] between January 2021 and July 2023, which contain 1,013 vulnerabilities from 251 projects. For the testing set, we used the vulnerabilities identified after July 2023 to avoid data leakage, which contains 51 vulnerable code segments and 51 non-vulnerable

code segments from 11 projects. The non-vulnerable code segments are randomly chosen from the same projects that contain vulnerable code segments, and they have similar complexity and lengths to the vulnerable code segments.

For Java, we collected data from CWE and CVE. To build the knowledge database, we used 77 CWEs from CWE websites, which are for software written in Java [8]. Unlike Solidity, where there is no bug report from the auditing platform, we use the knowledge of weaknesses from CWE directly. For each item in CWE, we collect the ID, title, description, mitigation, and code examples to build the knowledge database. Similarly, one database is indexed with code and another with the functional description. For the testing part, we collected 46 CVEs for Java, with both vulnerable and fixed versions, from 2013 to 2022.

To avoid data leakage, for Solidity, all the data in the testing sets were published after the knowledge cutoff date of the LLMs. For Java, since the code segments are from real-world projects prior to 2022, they may be contained in the pre-training dataset of LLMs. To mitigate the risk of data leakage, we used GPT-4 to systematically rewrite the code segments with different function names, variable names, and comments, while strictly maintaining the same semantics, and we did not change the statements at all.

For knowledge retrieval, we use FAISS [36] to construct the vector database, and we set the top-K to retrieve the top-3 most relevant pieces of knowledge per query. In FAISS, the query is embedded and calculates the dot product with all the vectors in the database; the top-K vectors with the highest dot products are returned as the result. Besides, to minimize the impact of randomness on the result, the case without knowledge will be executed three times, which is the same as the case with knowledge. As a result, for Solidity, although there are only 51+51 code segments, they generate diverse test cases for different combinations of three knowledge retrievals, two prompt schemes, two context variations, and four different models, amounting to a total of 4,896 ( $102 \times 3 \times 2 \times 2 \times 4$ ) test cases. And for Java, there are a total of 4,416 ( $92 \times 3 \times 2 \times 2 \times 4$ ) test cases.

## 4.2 LLMs Evaluated and Their Configurations

For LLMs, we aim to benchmark the most advanced proprietary and open-source models available at the time of our evaluation (between November 2023 and January 2024). Therefore, from the LLMs listed in Table 1, we select gpt-4-1106-preview as the state-of-the-art proprietary model and choose mixtral-7b-instruct and llama3-8b-instruct as the open-source models, based on the background introduced in §2. We also used gpt-3.5-turbo-0125, which is a widely used free commercial model.

We use the OpenAI API to interact with gpt-4-1106-preview and gpt-3.5-turbo-0125, and the Replicate API to interact with mixtral-7b-instruct, llama3-8b-instruct. We ad-

here to the default model configuration provided by the model providers, as we cannot predict the parameter specifications users might choose in practice. The configurations are as follows:

- **GPT-3.5**: Temperature: 1, Top-p: 1, Frequency penalty: 0.0, Presence penalty: 0.0.
- **GPT-4**: Temperature: 1, Top-p: 1, Frequency penalty: 0.0, Presence penalty: 0.0.
- **Mixtral**: Temperature: 0.7, Top-p: 0.95, Top-k: 50, Frequency penalty: 0.0, Presence penalty: 0.0.
- **Llama 3**: Temperature: 0.7, Top-p: 0.95, Presence penalty: 0.0.

For simplicity, going forward, we use the above model names to refer to the specific model instances tested in this paper.

For the choice of temperature, we do not want to sacrifice the LLM's inherent creativity for less randomness (e.g., by setting the temperature to 0). Therefore, we use the models' default settings, which are supposed to be widely used, and run each scenario three times—top-3 knowledge retrieved for each testing via RAG or repeated three times without knowledge supply. We could run more times each but the cost of testing LLMs (e.g., \$400 for GPT-4, \$40 for GPT-3.5) is high. Furthermore, we argue that potential randomness in individual cases is not an issue for our evaluation. First, as explained in §1, our research objective is not to obtain a precise performance number for individual models; instead, we are concerned only with the relative improvement by LLM's different assisted capabilities (e.g., knowledge retrieval and context supplementation). Second, as mentioned in §4.1, we have 9,312 diverse test cases (4,656 without considering context variation), which are sufficient to show statistical patterns. Result Scope. As LLM4Vuln's current implementation specifically targets different programming languages, the findings to be reported in §5 are primarily applicable to Solidity and Java. However, it may not necessarily align with results when testing LLM4Vuln for other programming languages.

#### 5 Evaluation

In this section, we evaluate how LLMs' vulnerability reasoning could be enhanced when combined with the enhancement of other capabilities under the framework of LLM4Vuln. Specifically, we use the experimental setup described in §4 and the standards for calculating True Positives (TP), True Negatives (TN), False Positives (FP), False Negatives (FN), and False Positive-Type (FP-Type), as defined in §3.4.

Table 3 presents the overall results, which includes the raw results of TP, TN, FP, FN, and FP-type under different combinations of knowledge, context, and prompt schemes, as well as the calculated precision, recall, and F1 score. Based on these results, we perform a correlation analysis and answer five research questions (RQs) from §5.1 to §5.4. Note that the results related to the two open-source models are primarily analyzed in §5.4, as they mainly serve for comparison with

Table 3: Raw results of TP, FP, FN, and FP-type (abbreviated as "FPt") along with the calculated Precision (abbreviated as "P"), Recall, and F1 score ("F1") under different combinations of knowledge, context, prompt scheme for Solidity and Java.

	Solidity																	
	Raw							CoT										
			TP	FP	TN	FN	FPt	P	Recall	F1	TP	FP	TN	FN	FPt	P	Recall	F1
	W/O Festers Victorials de s	C	14	147	6	5	134	4.75	9.15	6.25	16△	152▽	1▽	1△	136▽	5.26△	10.46△	7.00△
\sigma	W/O Extra Knowledge	N	18	137	16	5	130	6.32	11.76	8.22	16▽	153▽	0▽	0△	137▽	5.23▽	10.46▽	6.97▽
F-3.	W/ Original Vuln Report	C	26	151	2	6	121	8.72	16.99	11.53	17▽	146△	7△	5△	131▽	5.78▽	11.11▽	7.61▽
GPT-	W/ Original Valli Report	N	18	149	4	3	132	6.02	11.76	7.96	17▽	150▽	3▽	1△	135▽	5.63▽	11.11▽	7.47▽
~	W/ Summarized Knowledge	С	10	129	24	32	111	4.00	6.54	4.96	22△	144▽	9▽	12△	119▽	7.72△	14.38△	10.05△
	W/ Summarized Knowledge	N	21	121	32	17	115	8.17	13.73	10.24	17▽	131▽	22▽	15△	121▽	6.32▽	11.11▽	8.06▽
	W/O Extra Knowledge	C	26	151	2	0	127	8.55	16.99	11.38	35△	147△	6△	5▽	113△	11.86△	22.88△	15.62△
1_	W/O Extra Kilowieuge	N	34	153	0	0	119	11.11	22.22	14.81	26▽	134△	19△	9▽	118△	9.35▽	16.99▽	12.06▽
1 £	W/ Original Vuln Report	С	12	149	4	2	139	4.00	7.84	5.30	15△	146△	7△	3▽	135△	5.07△	9.80△	6.68△
1 &		N	18	146	7	2	133	6.06	11.76	8.00	16▽	139△	14△	10▽	127△	5.67▽	10.46▽	7.36▽
	W/ Summarized Knowledge	С	28	105	48	29	96	12.23	18.30	14.66	33△	88△	65△	45▽	75△	16.84△	21.57△	18.91△
		N	29	113	40	34	90	12.50	18.95	15.06	29	78△	75△	45▽	79△	15.59△	18.95	17.11△
	W/O Extra Knowledge	С	6	56	97	93	54	5.17	3.92	4.46	11△	61▽	92▽	77△	65▽	8.03△	7.19△	7.59△
-	W/O Extra Knowledge	N	7	85	68	87	59	4.64	4.58	4.61	9△	76△	77△	96▽	48△	6.77△	5.88△	6.29△
l E	W/ Original Vuln Report	С	11	77	76	85	57	7.59	7.19	7.38	13△	80▽	73▽	76△	64▽	8.28△	8.50△	8.39△
Mixtral	w/ Original vulli Report	N	13	104	49	45	95	6.13	8.50	7.12	19△	79△	74△	72▽	62△	11.88△	12.42△	12.14△
-	W/ Summarized Knowledge	С	8	85	68	76	69	4.94	5.23	5.08	20△	61△	92△	69△	64△	13.79△	13.07△	13.42△
	w/ Summarized Knowledge	N	12	81	72	82	59	7.89	7.84	7.87	23△	88▽	65▽	58△	72▽	12.57△	15.03△	13.69△
	W/O Extra V navilada	С	17	153	0	0	136	5.56	11.11	7.41	16▽	152△	1△	0	137▽	5.25▽	10.46▽	6.99▽
1 60	W/O Extra Knowledge	N	15	153	0	0	138	4.90	9.80	6.54	12▽	152△	1△	0	141▽	3.93▽	7.84▽	5.24▽
na	W/ Oniginal Vivle Danger	С	11	151	2	3	139	3.65	7.19	4.85	9▽	151	2	3	141▽	2.99▽	5.88▽	3.96▽
Llama	W/ Original Vuln Report	N	11	152	1	0	142	3.61	7.19	4.80	8	150△	3△	0	145	2.64▽	5.23▽	3.51▽
-	W/ Summarized Vnowledge	С	19	150	3	2	132	6.31	12.42	8.37	22△	117△	36△	28▽	103△	9.09△	14.38△	11.14△
	W/ Summarized Knowledge	N	21	151	2	6	126	7.05	13.73	9.31	23△	142△	11△	8▽	122△	8.01△	15.03△	10.45△

	Java																	
Raw									CoT									
			TP	FP	TN	FN	FPt	P	Recall	F1	TP	FP	TN	FN	FPt	P	Recall	F1
	W/O Extra Knowledge	С	28	102	36	32	78	13.46	20.29	16.18	27▽	125▽	13▽	11△	100▽	10.71▽	19.57▽	13.85▽
\v.	W/O Extra Kilowicuge	N	34	101	37	27	77	16.04	24.64	19.43	26▽	125▽	13▽	11△	101▽	10.32▽	18.84▽	13.33▽
GPT-3.5	W/ Original Vuln Report	C	3	105	33	33	102	1.43	2.17	1.72	3	93△	45△	42▽	93△	1.59△	2.17	1.83△
1 25	W/ Original Valli Report	N	8	118	20	23	107	3.43	5.80	4.31	2▽	104△	34△	38▽	98△	0.98▽	1.45▽	1.17▽
~	W/ Summarized Knowledge	C	3	101	37	41	94	1.52	2.17	1.79	6△	109▽	29▽	25△	107▽	2.70△	4.35△	3.33△
	Wy Summarized Knowledge	N	5	104	34	37	96	2.44	3.62	2.92	5	115▽	23▽	19△	114▽	2.14▽	3.62	2.69▽
	W/O Extra Knowledge	C	30	113	25	35	73	13.89	21.74	16.95	41△	105△	33△	28△	69△	19.07△	29.71△	23.23△
4	W/O Extra Rillowledge	N	28	112	26	35	75	13.02	20.29	15.86	43△	111△	27△	22△	73△	18.94△	31.16△	23.56△
GPT-4	W/ Original Vuln Report	C	0	18	120	124	14	0.00	0.00	-	3△	15△	123△	125▽	10△	10.71△	2.17△	3.61△
15	W Original Valli Report	N	3	16	122	120	15	8.82	2.17	3.49	3	14△	124△	128▽	7△	12.50△	2.17	3.70△
	W/ Summarized Knowledge	C	5	29	109	97	36	7.14	3.62	4.81	4▽	14△	124△	118▽	16△	11.76△	2.90▽	4.65▽
	Wy Summarized Knowledge	N	6	39	99	107	25	8.57	4.35	5.77	3▽	21△	117△	105△	30▽	5.56▽	2.17▽	3.12▽
	W/O Extra Knowledge	C	5	38	100	99	34	6.49	3.62	4.65	2▽	32△	106△	114▽	22△	3.57▽	1.45▽	2.06▽
=	W/O Extra Kilowicuge	N	6	41	97	97	35	7.32	4.35	5.45	6	39△	99△	105▽	27△	8.33△	4.35	5.71△
X E	W/ Original Vuln Report	С	4	21	117	118	16	9.76	2.90	4.47	3▽	20△	118△	113△	22▽	6.67▽	2.17▽	3.28▽
Mixtral	vvi Originar vani Report	N	2	29	109	111	25	3.57	1.45	2.06	3△	38▽	100▽	114▽	21△	4.84△	2.17△	3.00△
1	W/ Summarized Knowledge	C	4	42	96	98	36	4.88	2.90	3.64	11△	56▽	82▽	91△	36	10.68△	7.97△	9.13△
	Wy Summarized Knowledge	N	4	36	102	102	32	5.56	2.90	3.81	10△	57▽	81▽	84△	44▽	9.01△	7.25△	8.03△
	W/O Extra Knowledge	C	10	138	0	2	126	3.65	7.25	4.85	11△	129△	9△	16▽	111△	4.38△	<b>7.97</b> △	5.66△
ω	ກ	N	11	138	0	0	127	3.99	7.97	5.31	6▽	125△	13△	16▽	116△	2.43▽	4.35▽	3.12▽
ma	W/ Original Vuln Report	C	1	112	26	17	120	0.43	0.72	0.54	1	59△	79△	60▽	77△	0.73△	0.72	0.73△
Llama	11, Griginai vani Report	N	1	123	15	16	121	0.41	0.72	0.52	1	78△	60△	61▽	76△	0.65△	0.72	0.68△
-	W/ Summarized Knowledge	C	6	134	4	2	130	2.22	4.35	2.94	3▽	107△	31△	29▽	106△	1.39▽	2.17▽	1.69▽
	W/ Summarized Knowledge	N	9	133	5	2	127	3.35	6.52	4.42	5▽	115△	23△	34▽	99△	2.28▽	3.62▽	2.80▽

- 1. "C" and "N" represent the results with context and without context, respectively.
- 2.  $\triangle$  and  $\nabla$  indicate better or worse values compared to the Raw column.
- 3. The best result within each combination of knowledge, context, prompt scheme, and model is highlighted in bold.

GPT models. Lastly, we conduct a pilot study in §5.5 on using LLM4Vuln to test new projects for zero-day vulnerabilities.

## 5.1 RQ1: Effects of Knowledge Enhancement

In this RQ, we aim to evaluate the effects of knowledge enhancement mechanisms introduced by LLM4Vuln in §3.1.

A surprising finding is that knowledge enhancement does not always have the same impact across different programming languages, such as Solidity and Java, which we tested. According to Table 3, we observe that vulnerability knowledge significantly improves LLMs' reasoning on Solidity vulnerabilities. In every combination, models with knowledge (either W/ Summarized Knowledge or Original Vuln Report) outperform those without any extra knowledge (W/O Extra *Knowledge*) in terms of F1 score. However, the opposite is true for Java, where in most combinations, models exhibit superior performance without extra knowledge, except for the combination of Mixtral with the CoT scheme. This phenomenon could be attributed to this major reason: Solidity has significantly more logic vulnerabilities compared to traditional languages such as C/C++ and Java, as described in [70]. Detecting these requires fine-grained vulnerability knowledge to be supplied to LLMs. In contrast, traditional languages have well-organized Common Weakness Enumeration (CWE) vulnerability categories, which have been adopted by LLMs during their pre-training phase. This can be indirectly inferred from the fact that significantly more TPs are identified in Java without extra knowledge compared to Solidity. As a result, supplying additional specific vulnerability knowledge may simply distract LLMs' attention [61] in the Java scenario.

We now take a closer look at the results. For Solidity, summarized knowledge achieves the best performance, exhibiting higher precision (in 7 out of 8 model-prompt combinations) and a higher F1-score (in 7 out of 8 model-prompt combinations) than the model without extra knowledge or with the original vulnerability report. For recall, combinations with summarized knowledge provide the highest recall in 4 out of 8 model-prompt combinations, while the model without extra knowledge achieves the highest recall in 2 out of 8 model-prompt combinations, and the model with the original vulnerability report achieves the highest recall in the remaining two combinations. Both the highest precision and recall are produced by the GPT-4 model. In particular, the highest F1 score of 18.91% was achieved by the combination of *GPT-4 W/ Summarized Knowledge*, with CoT, and with context.

In all 16 model-prompt-context combinations, compared to those without extra knowledge, the combinations with summarized knowledge have higher precision in 14 of them, higher recall in 13 of them, and a higher F1-score in 15 of them. Summarized knowledge improves TP cases and reduces FP cases, which leads to increased precision, recall, and F1-score. For combinations with the original vulnerability report, the precision is higher than those without extra knowledge in 7 out of 16 model-prompt combinations, the recall is higher in 7 out of 16, and the F1-score is higher in 7 out of 16. The original vulnerability report slightly increases both the TP and FP cases, leading to an unstable impact on precision, recall, and F1-score.

In contrast, for Java, models without extra knowledge perform better than those with knowledge enhancement, showing higher precision, recall, and F1-score (in 6, 7, and 7 out of 8 model-prompt combinations, respectively). In most combinations, the addition of knowledge reduces TP cases and FP

cases and introduces more FN cases, which leads to decreased precision, recall, and F1-score.

Regardless of the programming language, we further analyze the differing impacts of summarized knowledge and original vulnerability reports. Most of raw knowledge is lengthy and rich in detail. Due to the attention mechanism [61] of LLMs, these abundant details can easily distract an LLM's focus, leading it to reach a positive yet incorrect result, which increases the number of FP and FP-type cases. In contrast, summarized vulnerability knowledge is concise and contains only the information necessary to detect a specific vulnerability. Hence, when provided with summarized knowledge, LLMs tend to be more focused and are less likely to generate false positives, as indicated by the lower number of FP for models with Summarized Knowledge in Table 3.

**Finding 1:** Three sub-findings on the effects of knowledge enhancement on LLMs' vulnerability reasoning:

- (a) Knowledge enhancement has diverse impacts across different programming languages;
- **(b)** Positive impacts are observed in languages (e.g., Solidity) with more logic vulnerabilities, while negative impacts may occur in traditional languages (e.g., Java) that have well-organized CWE categories;
- (c) Regardless of the language, summarized knowledge improves LLMs' vulnerability reasoning more than original vulnerability reports.

#### 5.2 RQ2: Effects of Context Supplementation

In this RQ, we aim to evaluate the effects of context supplementation provided by LLMs' capability of invoking tools, as introduced in §3.2. We present all the results with context supplementation (the "C" rows) and without context supplementation (the "N" rows) for all combinations of knowledge, prompt schemes, and models in Table 3.

According to Table 3, on Solidity and Java, out of 48 modelprompt-knowledge combinations, 27 show higher precision, 17 show higher recall, and 24 show a higher F1 score with context supplementation. This indicates that context supplementation does not have a stable effect on the performance of LLMs in detecting vulnerabilities. When comparing the number of TP and FP cases, we find that in 23 combinations the number of TP is reduced with context supplementation, 17 is increased, and 8 remain the same. For FP cases, 26 combinations show a decrease, 18 show an increase, and 4 remain the same. This suggests that context supplementation may cause LLMs to provide more conservative results, which leads to a reduction in positive cases. In addition, additional context may not necessarily enhance reasoning abilities and could introduce extraneous information, potentially distracting LLMs from accurately identifying vulnerabilities.

**Finding 2:** Supplying context may not always enhance LLMs' ability to reason about vulnerabilities. It could also lead to distractions, hindering LLMs from accurately identifying vulnerabilities.

## 5.3 RQ3: Effects of Different Prompt Schemes

In this RQ, we aim to investigate the effects of different prompt schemes, specifically CoT prompts as introduced in §3.3, on LLMs' vulnerability reasoning.

For different prompt schemes, we observe that prompts with CoT could provide better performance than the original prompt. Among 48 combinations, the prompt with CoT has higher TP in 21 combinations, lower FP in 32 combinations, higher TN in 32 combinations, lower FN in 20 combinations, and lower FP-type in 27 combinations. Although the impact on TP, FN, and FP is not significant, the changes in TN and FP-type already have a significant impact on the performance of the model. In addition, 28 combinations have higher precision, 21 combinations have higher recall, and 26 combinations have a higher F1 score. For recall, there are also 7 combinations with the same recall, and another 21 combinations have a lower recall. This improvement is likely because LLMs generate new tokens based on existing ones, and Pre-CoT prompts LLMs to conduct reasoning according to functionality before providing an answer, leading to more reasonable outcomes in vulnerability detection.

**Finding 3:** The CoT prompt scheme can improve the precision and recall of LLMs' vulnerability reasoning in most scenarios. However, it does not have a consistent impact on recall improvement.

#### 5.4 RQ4: Performance with Different Models

In this RQ, we aim to evaluate the vulnerability reasoning capability of other models and determine whether the chain-of-thought prompt scheme is also effective for them. We have chosen two state-of-the-art open-source models for our evaluation: Mixtral and Llama 3, as well as the commonly used GPT-3.5/GPT-4 model. Their detailed configurations were previously introduced in §4.2.

For different models, most factors have a similar impact on the performance of the models. For example, the knowledge supply has a similar impact on the performance of the models. However, the performance of the models differs, which may be attributed to the different training data and the design purposes of the models.

For Mixtral, both the number of TP and FP are lower than those for GPT-3.5, GPT-4, and Llama 3, as shown in Table 3. And it has higher numbers of TN and FN. This leads to a significant decrease in recall and a low F1-score. Across all

12 combinations of prompt schemes, context supplements, and knowledge supplements, the recall is less than 16% for Solidity and less than 8% for Java. The F1-score is below 14% for Solidity and 10% for Java. After knowledge supply, the recall and F1-score of Mixtral are slightly improved.

Compared to GPT-4, Llama 3 exhibits a higher number of positive cases, including TP, FP, and FP types. In some extreme cases (*Llama3 W/O Extra Knowledge, Raw prompt, without context*), Llama 3 even gives 0 TN and 0 FN answers, arguing that all examples are vulnerable. As a result, Llama 3 has very low precision (the lowest of 0.65%) and F1-score (the lowest of 0.68%). Unlike GPT-3.5, GPT-4, and Mixtral, after using CoT prompts, the precision and F1-score of Llama 3 are not significantly improved. In some combinations, the precision and F1-score are even lower than the original values.

**Finding 4:** Context supplements, knowledge supplements, and prompt schemes have a similar impact on the performance of different models. However, for models with poor capability in vulnerability detection, the impact of these factors may not be significant.

## 5.5 RQ5: Testing for Zero-Day Vulnerabilities

In this RQ, we deployed LLM4Vuln's approach to the web service of our industry partner, a Web3 security company. As a result, in this RQ, we only discuss the new zero-day vulner-abilities found by LLM4Vuln in Solidity projects. LLM4Vuln was used to audit real-world smart contract projects, and all the outputs, after a brief manual review to filter out factual errors, were submitted to the Secure3 community for confirmation. We submitted a total of 29 issues to these four projects, with 14 issues confirmed by the community, which are Apebond, Glyph AMM, StakeStone, and Hajime. Details of the projects and bounties can be found in Table 4. From these four programs combined, we received a total bounty of \$3,576, demonstrating the practicality of LLM4Vuln.

In the rest of this section, we will conduct case studies on the confirmed issues in the *Apebond* project [2], which involves a set of contracts for single transaction token swaps, liquidity provision, and bond purchases. The audit report for *Apebond* is available at [3] and does not include the real names of the auditors.

The first case involves an iteration without proper checks for duplicate entries, potentially leading to financial losses. The source code is shown in Figure 6. The function \_routerSwapFromPath is designed to execute a token swap operation using the input parameter \_uniSwapPath, which is expected to contain a swapping path \_uniSwapPath.path indicating the series of token conversions to be executed. If the input array contains duplicate entries, it will result in unnecessary token conversions, and the fees paid for these duplicated conversions will be lost. Using LLM4Vuln, we matched the

Table 4: Projects audited in RQ5.

Project	Bounty (\$)	Submitted	Confirmed
Apebond	376	12	4
Glyph AMM	329	6	4
StakeStone	2281	9	5
Hajime	590	2	1
Total	3,576	29	14

```
1 function _routerSwapFromPath(
       SwapPath memory _uniSwapPath,
       uint256 _amountIn,
 4
       address _to,
       uint256 _deadline
   ) private returns (uint256 amountOut) {
       require(_uniSwapPath.path.length >= 2, "SoulZap:
            need path0 of >=2");
 8
       address outputToken = _uniSwapPath.path[
             _uniSwapPath.path.length - 1];
 9
       uint256 balanceBefore = _getBalance(IERC20(
            outputToken), _to);
10
       _routerSwap(
11
           _uniSwapPath.swapRouter,
12
           _uniSwapPath.swapType,
13
           _amountIn,
14
           _uniSwapPath.amountOutMin,
15
           uniSwapPath.path,
16
           to,
17
           _deadline
18
19
       amountOut = getBalance(IERC20(outputToken), to)
            - balanceBefore:
20 }
```

Figure 6: Case 1 - Lack of Duplication Check for Input Array.

functionality of the code with the knowledge that "For any functionality that involves processing input arrays, especially in smart contracts or systems managing assets and tokens, it's crucial to implement stringent validation mechanisms to check for duplicate entries." The full details of this knowledge are available in Knowledge 1 in Appendix C.

The second case, as shown in Figure 7, involves a precision calculation error that could lead to financial loss. In lines 7 and 8, the function get SwapRatio calculates the underlying balances of the swap tokens. This process includes normalization of precision, but it incorrectly assumes that the precision of the input token is always 18 decimal places. However, when obtaining price ratios from other oracles, the precision may vary and not always be 18 decimal places. This incorrect assumption about precision can lead to miscalculation of the swap ratio, potentially causing the user to gain tokens that do not belong to them or lose a number of tokens. With LLM4Vuln, we matched the functionality of the code with the knowledge that "The vulnerability stems from an incorrect handling of decimal precision while calculating the price ratio between two oracles with different decimals." The full details of this knowledge are available in Knowledge 2 in Appendix C.

Similarly, as shown in Figure 8, the function

```
function getSwapRatio(
       SwapRatioParams memory swapRatioParams
   ) internal view returns (uint256 amount0, uint256
        amount1) {
4
5
       vars.token0decimals = ERC20(address(
           swapRatioParams.token0)).decimals();
       vars.token1decimals = ERC20(address(
           swapRatioParams.token1)).decimals();
7
       vars.underlying0 = _normalizeTokenDecimals(vars.
           underlying0, vars.token0decimals);
8
       vars.underlying1 = _normalizeTokenDecimals(vars.
           underlying1, vars.token1decimals);
9
       // More code
10
11 function _normalizeTokenDecimals(
      uint256 amount,
12
13
       uint256 decimals
14
    internal pure returns (uint256) {
       return amount * 10 ** (18 - decimals);
15
16
```

Figure 7: Case 2 - Precision Calculation Error Type I.

```
function pairTokensAndValue(
        address token0,
3
        address token1.
        uint24 fee,
        address uniV3Factory
   ) internal view returns (uint256 price) {
6
        // More Code
8
        uint256 sqrtPriceX96;
9
        (sqrtPriceX96, , , , ,
                                      ) = IUniswapV3Pool(
              tokenPegPair).slot0();
        uint256 tokenODecimals = getTokenDecimals(tokenO);
uint256 tokenDecimals = getTokenDecimals(tokenI);
10
11
12
        if (token1 < token0) price = (2 ** 192) / ((
    sqrtPriceX96) ** 2 / uint256(10 ** (</pre>
              token0Decimals + 18 - token1Decimals)));
        else price = ((sqrtPriceX96) ** 2) / ((2 ** 192) /
13
               uint256(10 ** (token0Decimals + 18 -
              token1Decimals)));
14 }
```

Figure 8: Case 3 - Precision Calculation Error Type II.

pairTokensAndValue is responsible for calculating the price of tokens using sqrtPriceX96 obtained from a UniswapV3Pool. However, this function also erroneously assumes that the precision of sqrtPriceX96 is always 18 decimal places, which could result in unplanned benefits or loss of funds. The knowledge matched in LLM4Vuln for this scenario is "The vulnerability occurs when calculating the squared root price of a position in a liquidity pool with tokens having different decimal values." While two matched knowledge from cases 2 and 3 are not identical - the latter specifically mentions the "squared root price" - they are semantically similar and both applicable to describing the same type of vulnerability. The full details of this knowledge are available in Knowledge 3 in Appendix C.

In Figure 9, the function \_zap divides the input amount (amountIn) equally between amount0In and amount1In on lines 9 and 10. However, the actual token reserve ratio in the pool may not be 1:1. This discrepancy can lead to an imbalanced provision of liquidity when addLiquidity is

```
function zap (
       ZapParams memory zapParams,
3
       SwapPath memory feeSwapPath,
       bool takeFee
   ) internal whenNotPaused
          Verify and setup
       if (zapParams.liquidityPath.lpType == LPType.V2) {
           // some checks
           vars.amount0In = zapParams.amountIn / 2;
10
           vars.amount1In = zapParams.amountIn / 2;
11
12
          More code .....
13
       if (zapParams.liquidityPath.lpType == LPType.V2) {
14
            (vars.amount0Lp, vars.amount1Lp, ) =
                IUniswapV2Router02(
15
                zapParams.liquidityPath.lpRouter
16
           ).addLiquidity(
17
                    zapParams.token0,
18
                    zapParams.token1,
19
20
               );
21
       // More code
```

Figure 9: Case 4 - Funding Allocation Error.

called on line 16, as the token pair might require a different ratio for optimal liquidity provision. This vulnerability can disrupt the equilibrium of liquidity pools and cause traders to lose tokens. The knowledge matched in LLM4Vuln for this case is "The fundamental vulnerability occurs when liquidity providers add liquidity to a pool of two tokens, and the token amounts provided have different proportions as compared to the existing liquidity pool. The contract uses the smaller of these proportions to calculate the amount of LP tokens minted." While this knowledge does not precisely describe the vulnerability, as there is no smaller proportion in this specific case, it can still be useful in detecting the vulnerability when combined with the reasoning ability of LLMs. The full details of this knowledge are available in Knowledge 4 in Appendix C.

From the above four cases, it is evident that knowledge supplements in LLM4Vuln can aid in detecting vulnerabilities, even if the vulnerability does not exactly match the knowledge in the vector database. Among these four cases, only the first can be detected by static analysis tools, while the other three are logic bugs closely related to business logic. With the enhancement of knowledge, LLM4Vuln demonstrates its capability to detect bugs in real-world projects that are not identified by existing tools.

#### 6 Discussion and Future Work

#### 6.1 Lessons Learned

In this section, we summarize the key insights gained from our empirical study in §5 on using LLMs for detecting vulnerabilities in smart contracts, along with some recommendations for enhancing performance.

**Selection of Models.** Although both open source and commercial models perform similarly for different types of enhancements when performing vulnerability detection tasks, models that have poor vulnerability detection capabilities may not benefit significantly from these enhancements. To make the most of these enhancements, it is better to choose a model that already has a certain vulnerability detection capability.

Context Supplement. The context supplement introduces more noise while helping LLMs improve their understanding of the code's functionality and business logic. Too long contexts that are not relevant to the vulnerability can also lead to distraction for the LLMs, which in turn affects their results. Therefore, when using LLM for code auditing, only necessary and relevant context should be provided.

**Knowledge Enhancement.** Enhancing knowledge is crucial for helping LLMs better understand code and vulnerabilities. Matching code with knowledge is complex, and an inadequate matching algorithm could lead to semantic loss. An algorithm capable of accurately preserving or translating the semantic information of mathematical symbols in the code to natural language for matching knowledge is essential.

**Prompt Scheme Selection.** Chain-of-thought prompt schemes can significantly affect LLMs' performance. When designing prompt schemes, it is important to break down the tasks into simpler sub-tasks that LLMs can easily solve.

## 6.2 More Accurate Knowledge Retrieval

In this paper, we ensure the supplied knowledge is the same for each case within the same type of knowledge supply scenarios for a fair benchmark. Nevertheless, more accurate knowledge retrieval could lead to more powerful LLM-based vulnerability detection. Here we manually verify the accuracy of the knowledge retrieval used in our evaluation and leave more accurate knowledge retrieval to future work.

Specifically, we manually check whether the retrieved knowledge is relevant to the ground truth for the positive cases. For Solidity, we randomly sampled 100 cases and found that 68 of them have retrieved knowledge relevant to the ground truth. This also explains why the precision and recall of the LLMs increase when the knowledge base is attached. In these cases, vulnerabilities related to high-level semantics have a higher probability of being retrieved. In contrast, vulnerabilities related to low-level semantics, such as integer overflow, are less likely to be retrieved. On Java, only 36 out of 100 cases have relevant knowledge, resulting in worse performance of the LLMs with a knowledge base attached. Vulnerabilities like XSS and SQL injection are more likely to be retrieved, while vulnerabilities like SSRF and CSRF are harder to match. Most vulnerabilities for Java are not related to business logic and are harder to match with functionality.

Although the knowledge retrieval part does not always provide the exact same vulnerabilities as the ground truth, which is an extremely hard task, it is still useful for the LLMs to learn from the retrieved knowledge. As claimed in RQ5 and Appendix C, as long as the extracted knowledge has a certain similarity to the actual vulnerability, the LLM is more likely to identify the correct vulnerability.

## **6.3** Covering More Programming Languages

Our evaluation of LLMs is on Solidity, the most popular language for smart contracts, and Java, one of the most popular languages for general tasks. Hence, the vulnerability knowledge base and other related tools are designed for Solidity and Java. Nevertheless, LLM4Vuln has the potential to be adaptable to other languages, such as C/C++, Rust, JavaScript, and others. Evaluating LLM4Vuln on other languages is beyond the scope of this paper. In this section, we provide some suggestions for applying LLM4Vuln to other programming languages. Specifically, it is necessary to compile a vulnerability knowledge base for the target language and implement corresponding tool-invoking function calls, such as call graph construction. These function calls should be tailored based on the specific syntax and semantics of each language. The existing set of function calls could also be expanded to include data flow analysis and symbolic execution, applicable across multiple languages.

#### 7 Related Work

**LLM-based Vulnerability Detection.** Vulnerability detection has been a long-standing problem in software security. Traditional methods rely on predefined rules or fuzz testing, which are usually incomplete and struggle to detect unknown vulnerabilities. In recent years, with the development of codebased LLMs [52,58], researchers have proposed many methods to detect vulnerabilities using LLMs. For example, Thapa *et al.* [58] explored how to leverage LLMs for software vulnerability detection. Alqarni *et al.* [14] introduced a novel model fine-tuned for detecting software vulnerabilities. Tang *et al.* [57] proposed methods that utilize LLMs to detect software vulnerabilities, combining sequence and graph information to enhance function-level vulnerability detection. Hu *et al.* [33] proposed a framework that employs LLMs' roleplaying to detect vulnerabilities in smart contracts.

Some researchers apply LLMs to fuzz testing for vulnerability detection. For example, Deng *et al.* [24] introduced TitanFuzz to leverage LLMs to generate input cases for fuzzing deep learning libraries. FuzzGPT [25] is another work that uses LLMs to synthesize unusual programs for fuzzing vulnerabilities. Meng *et al.* [47] proposed an LLM-based protocol implementation fuzzing method called ChatAFL. Xia *et al.* [66] presented Fuzz4All, a tool that employs LLMs to generate fuzzing inputs for all kinds of programs.

Additionally, there are also studies combining LLMs with existing static analysis methods. For example, Sun *et al.* [56]

combined GPT with static analysis to detect logic vulnerabilities in smart contracts. Li *et al.* [42] proposed an automated framework to interface static analysis tools and LLMs. However, these studies focus only on detecting vulnerabilities and do not delve into the reasoning capabilities of LLMs or the impact of these capabilities on vulnerability detection. In this paper, we introduce LLM4Vuln, a unified framework to benchmark and explore the capability of LLMs' reasoning in vulnerability detection.

Benchmarking LLMs' Ability in Vulnerability Detection. Other researchers focus on evaluating the capability of LLMs' reasoning in vulnerability detection. For example, Thapa et al. [58] compared the performance of transformer-based LLMs with RNN-based models in software vulnerability detection. Chen et al. [18] conducted an empirical study to investigate the performance of LLMs in detecting vulnerabilities in smart contracts. David et al. [23] evaluated the performance of LLMs in security audits of 52 DeFi smart contracts. Khare et al. [37] benchmarked the effectiveness of LLMs in Java and C++ vulnerability detection. Gao et al. [31], Ullah et al. [60], Ding et al. [26] introduced diverse datasets of vulnerabilities and evaluated LLMs, deep learning-based methods, and traditional static analysis models in vulnerability detection. Additionally, LLMs have also been evaluated on the vulnerability repair task [50, 69]. However, these studies focus on the performance of individual LLM instances and their configurations. In contrast, we aim to explore the capability of LLMs' reasoning in vulnerability detection.

**Security-oriented LLMs.** Beyond being a language model, some studies have introduced vulnerability-specific or security-oriented models. For instance, Lacomis et al. [39] created corpora for renaming decompiled code, while Pal et al. [49] developed a model to predict the real variable names from decompilation outputs. Pei et al. [51] introduced a new mechanism of transformers for learning code semantics in security tasks. Chen et al. [19] improved decompilation results for security analysis, and Ding et al. [27] enhanced model performance with an execution-aware pre-training strategy. Gai et al. [30] focused on detecting anomalous blockchain transactions, and Guthula et al. [32] pre-trained a network security model on unlabeled network packet traces. Jiang et al. [35] and Li et al. [43] both presented LLMs for binary code analysis. Recently, Wang et al. [62] proposed SmartInv for smart contract invariant inference. While all of these studies focus on security-oriented LLMs, our work explores the general capabilities of LLMs, specifically decoupling their vulnerability reasoning from other capabilities..

#### 8 Conclusion

This paper proposes LLM4Vuln, a unified evaluation framework to decouple and enhance LLMs' reasoning about vulnerabilities. By applying LLM4Vuln to 194 Solidity and Java cases in 9,312 scenarios, we gained insights into the

effects of knowledge enhancement, context supplementation, and prompt schemes. Furthermore, our pilot study identified 14 zero-day vulnerabilities across four projects, resulting in a total of \$3,576 in bounties. This demonstrates an improved paradigm for LLM-based vulnerability detection via the framework of LLM4Vuln.

#### **Ethical Considerations**

In this section, we clarify the potential ethical considerations associated with this research.

**Authorized Vulnerability Detection:** The vulnerabilities for building knowledge database and evaluation are collected from public sources, such as bug bounty programs and GitHub issues. All vulnerability detection activities in RQ5 were conducted exclusively through formal invitations by vulnerability audit platforms. The testing environments were strictly offline deployed, ensuring that no unauthorized penetration testing was carried out. Furthermore, these activities did not interfere with the stability or functionality of any publicly deployed services.

**Responsible Disclosure:** All identified vulnerabilities were submitted to the respective vendors for confirmation before any public disclosure. The vulnerabilities mentioned in this paper were disclosed after receiving vendor confirmation and after appropriate patches or fixes were deployed, ensuring that no exposed vulnerabilities remained unaddressed prior to publication.

#### **Open Science Statement**

Our dataset and source code are open-sourced at https://anonymous.4open.science/r/LLM4Vuln/. There is a detailed instruction on how to reproduce our experiments inside the repository. However, since the knowledge database of Solidity is from our industry partner, we could not open-source them without their permission, and the summarized knowledge database of Solidity is not included in the repository. You can still use the rest of the dataset and source code to reproduce experiments for Java and Solidity vulnerabilities (except for models with summarized knowledge).

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## **Appendix**

## A Prompt for Summarizing the Functionalities and Root Causes from Vulnerability Reports

#### Prompt for Summarizing

#### **Summarize Functionalities**

Given the following vulnerability description, following the task:

- 1. Describe the functionality implemented in the given code. This should be answered under the section "Functionality:" and written in the imperative mood, e.g., "Calculate the price of a token." Your response should be concise and limited to one paragraph and within 40-50 words.
- 2. Remember, do not contain any variable or function or experssion name in the Functionality Result, focus on the functionality or business logic itself.

#### **Summarize Root Cause**

Please provide a comprehensive and clear abstract that identifies the fundamental mechanics behind a specific vulnerability, ensuring that this knowledge can be applied universally to detect similar vulnerabilities across different scenarios. Your abstract should:

- 1. Avoid mentioning any moderation tools or systems.
- 2. Exclude specific code references, such as function or variable names, while providing a general yet precise technical description.
- 3. Use the format: KeyConcept:xxxx, placing the foundational explanation of the vulnerability inside the brackets.
- 4. Guarantee that one can understand and identify the vulnerability using only the information from the VulnerableCode and this KeyConcept.
- 5. Strive for clarity and precision in your description, rather than brevity.
- 6. Break down the vulnerability to its core elements, ensuring all terms are explained and there are no ambiguities.
- By following these guidelines, ensure that your abstract remains general and applicable to various contexts, without relying on specific code samples or detailed case-specific information.

## **B** Prompt for Instruction Following and Auto-Annotation

## Prompt for Auto-Annotation

#### **Generate Type and Description**

I will give you some text generated by another LLM. But the format may be wrong. You must call the report API to report the result.

## Compare Types between Output and Ground Truth

You are a senior smart contract auditor. Now I will give you a ground truth of vulnerability, and a description written by an auditor. You need to help me identify whether the description given by the auditor contains a vulnerability in the ground truth. Please report the result using the function call.

Ground truth: {Ground Truth}

Description: {Output}

#### Reason FP

You are a senior smart contract auditor. I will give you a ground truth of vulnerability and a description written by an auditor. The auditor gives a false positive result. Please help me identify the reason and select one from the Available Options. Please report the result using the function call.

Ground truth: {Ground Truth}

Description: {Output}

Available Options: {Options}

#### Reason FN Type 1

You are a senior smart contract auditor. I will give you a ground truth of vulnerability and a description written by an auditor. The audit failed to find the vulnerability in the code. Please help me identify the reason and select one from the Available Options. Please report the result using the function call.

Ground truth: {Ground Truth}

Description: {Output}

Available Options: {Options}

#### **Options**

NeedOtherCode: choose this when the auditor needs other code to make the decision.NeedDetailAnalysis: choose this when the auditor needs more detailed analysis, such as dataflow or symbolic execution, to make the decision. WrongReasoning: choose this when the auditor made a wrong reasoning.Other: choose this when the reason is none of the above. You must call the report API to report the result.

## C Matched Knowledge in RQ5

Knowledge 1: Rigorous Validation Against Duplicate Entries in Input Arrays For any functionality that involves processing input arrays, especially in smart contracts or systems managing assets and tokens, it's crucial to implement stringent validation mechanisms to check for duplicate entries. This validation is necessary to prevent exploitation where duplicates in the input can lead to erroneous calculations, inflated balances, or disproportionate distribution of benefits. By ensuring that each entry in an input array is unique and correctly mapped, systems can avoid vulnerabilities that arise from improper handling of duplicate entries. This concept applies broadly across various functionalities and is essential for maintaining the integrity and security of systems handling valuable data or assets.

Knowledge 2: Incorrect handling of decimal precision in price ratio calculations The vulnerability stems from a incorrect handling of decimal precision while calculating the price ratio between two oracles with different decimals. The current implementation assumes that the input price feeds will have a fixed decimal value (e.g., 8 decimals) and performs calculations accordingly. However, when a price feed with a different number of decimals is provided, it leads to inaccurate and, in some cases, completely incorrect results due to wrong math operations used in handling the decimals. The core issue lies in the assumption that all price feeds will have a fixed number of decimals and the subsequent calculations performed. In the problematic implementation, decimals are added and removed by a fixed amount based on this assumption, leading to the loss of precision when a different decimal value is used. This can impact the validity of the price ratio and have a cascading effect on other calculations dependent on this value. To mitigate this vulnerability, the implementation should properly handle price feeds with varying decimals. Instead of assuming a fixed number of decimals, the calculations should adapt to the actual number of decimals provided by the price feeds. By modifying the code that calculates the price ratio to account for varying decimals and correctly scaling the intermediate values, the vulnerability can be addressed, ensuring accurate price ratio calculations regardless of the number of decimals in the input price feeds.

**Knowledge 3:** Incorrect handling of token decimals when calculating the squared root price ratio in a liquidity pool, leading to inflated values for certain token

pairs and affecting pricing calculations. The vulnerability occurs when calculating the squared root price of a position in a liquidity pool with tokens having different decimal values. The price ratio calculation does not correctly handle the difference in token decimal values. Specifically, the issue occurs when the token1 decimal is strictly greater than the token decimal. In such cases, the calculated squared root price can be significantly inflated due to the hard-coded constant (1E9 or 10\*\*9) used for normalization, which does not take into account the difference between the token decimals. As a consequence of this miscalculation, functions that rely on the squared root price ratio, like getAmounts-ForLiquidity() and getTokenPrice(), can return inflated liquidity amounts and incorrect token prices. This issue can adversely affect the proper functioning of the liquidity pool and lead to imprecise calculations in token pricing and distribution. To mitigate this vulnerability, it is crucial to account for the difference in token decimals during the calculation of the squared root price ratio. Instead of using a fixed constant for normalization, the function should dynamically calculate normalization factors based on the difference between the token decimals. This ensures that the correct squared root price ratio is calculated and returned for various token pairs, leading to more accurate token prices and liquidity calculations.

Knowledge 4: Inaccurate token amount calculation in adding liquidity The fundamental vulnerability occurs when liquidity providers add liquidity to a pool of two tokens, and the token amounts provided have different proportions as compared to the existing liquidity pool. The contract uses the smaller of these proportions to calculate the amount of LP tokens minted. Due to this, there will be excess tokens that cannot be redeemed for the amount of LP tokens minted, effectively donating the extra tokens to the pool, which will be shared among all liquidity providers of the pool. This vulnerability is caused by the improper calculation of optimal token amounts based on user inputs, pool reserves, and the minimal LP tokens amount specified by the user, resulting in an undesired discrepancy in token proportions when providing liquidity. To mitigate this issue, it is recommended to enhance the token amount calculation mechanism while adding liquidity to a pool, similar to how it is handled in Uniswap V2 Router.