RealVul: Can We Detect Vulnerabilities in Web Applications with LLM?

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Abstract

The latest advancements in large language models (LLMs) have sparked interest in their potential for software vulnerability detection. However, there is currently a lack of research specifically focused on vulnerabilities in the PHP language, and challenges in extracting samples and processing persist, hindering the model's ability to effectively capture the characteristics of specific vulnerabilities. In this paper, we present RealVul, the first LLM-based framework designed for PHP vulnerability detection, addressing these issues. By vulnerability candidate detection methods and employing techniques such as normalization, we can isolate potential vulnerability triggers while streamlining the code and eliminating unnecessary semantic information, enabling the model to better understand and learn from the generated vulnerability samples. We also address the issue of insufficient PHP vulnerability samples by improving data synthesis methods. To evaluate RealVul's performance, we conduct an extensive analysis using five distinct code LLMs on vulnerability data from 180 PHP projects. The results demonstrate a significant improvement in both effectiveness and generalization compared to existing methods, effectively boosting the vulnerability detection capabilities of these models.

1 Introduction

Software vulnerabilities present substantial risks to the security and integrity of computer systems, networks, and data(Sausalito). In 2023, a staggering 28,902 vulnerabilities were publicly reported in the Common Vulnerabilities and Exposures (CVE) database(MITRE). PHP, recognized as the most prevalent and extensively utilized language in web applications, powers nearly 80% of the top ten million websites(W3Techs). This includes widely adopted platforms such as Facebook, Wikipedia, Flickr, and WordPress. Moreover, it has been instrumental in the development of over 3.3 million open-source projects on GitHub(Git). However, PHP is susceptible to common web security vulnerabilities, including SQL injection and cross-site scripting (XSS). Consequently, the imperative to effectively detect PHP software vulnerabilities has never been more pressing.

Traditional vulnerability detection methods, such as Static Application Security Testing (SAST) tools including CodeQL(Cod), RIPS(RIP), SonarQube(Son), Fortify SCA(for), and Checkmarx(che), are often constrained by the comprehensiveness and precision of their rule libraries. This limitation frequently results in a high incidence of false positives and negatives. And as a popular framework, CodeQL does not yet support PHP language. To address these issues, researchers have begun to explore the application of deep learning for vulnerability detection(Li et al., 2018; Zhou et al., 2019; Zou et al., 2019; Wang et al., 2020; Li et al., 2021; Chakraborty et al., 2020; Mirsky et al., 2023). These approaches extract code structure information in the form of Data Flow Graph (DFG) and Control Flow Graph (CFG), and input vulnerability samples into deep learning models for training. Concurrently, with the advancement of Large Language Modeling (LLM), studies focusing on the application of LLM to code vulnerability detection have started to surface(Fu and Tantithamthavorn, 2022; Wang et al., 2023a; Sun et al., 2024).

After reviewing the current research on applying deep learning or LLMs to vulnerability detection, we discovered: (1) As shown in Appendix A, existing LLM-based methods predominantly rely on vulnerability datasets in C/C++ languages for analysis, leaving a research gap in other language; (2) The majority of vulnerability datasets are collected through vulnerability fixes on GitHub(Chakraborty et al., 2020; Zhou et al., 2019; Nikitopoulos et al., 2021), which presents certain challenges in data

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collection. Our practical experience has shown that the samples in these datasets may not correlate appropriately with vulnerabilities; (3) Vulnerable code requires suitable preprocessing before being inputted into the model to reduce noise and highlight vulnerability features, but this aspect is often overlooked in existing research.

To address these issues, we propose RealVul, a new snippet-level PHP vulnerability analysis framework. First of all, RealVul extracts the real-world vulnerability dataset by identifying potential vulnerability trigger points from real-world projects, analyzing control flow and data flow, and proper data preprocessing methods. Then RealVul generates large semi-synthetic vulnerability dataset from real-world vulnerability dataset and projects. RealVul use this semi-synthetic dataset to fine-tune different LLMs including CodeT5(Wang et al., 2021), CodeT5+(Wang et al., 2023b), StarCoder2(Lozhkov et al., 2024), and CodeLlama(Roziere et al., 2023).

We evaluate RealVul on CWE-79 (XSS) and CWE-89 (SQL Injection), comparing RealVul with existing approaches. The results demonstrate that RealVul achieves reliable generalization performance while ensuring effectiveness, making our framework suitable for detecting PHP vulnerabilities in real-world projects.

Our main contributions are as follows:

- **LLM-based PHP Vulnerability Detection Framework.** To the best of our knowledge, RealVul is the first LLM-based framework to extract vulnerability dataset and detect PHP software vulnerabilities. It significantly enhances the ability of LLMs to detect vulnerabilities and implements scalable vulnerability detection based on robust generalization performance. (sec.3)

- **Dataset Collection and Preprocessing.** Different from previous dataset collection methods based on vulnerability repair, we extracted our new RealVul dataset from real-world projects by localizing potential vulnerability and program slicing, and we performed appropriate data preprocessing on it. This allows the model to perform better in the task of vulnerability detection. (sec.3.1 and sec.3.2)

- **Data Synthesis.** We present a new data synthesis method and generate a large semi-synthetic vulnerability dataset by inserting pure vulnerability samples into real-world projects devoid of vulnerabilities, which allows programming languages like PHP that lack sufficient vulnerability datasets to obtain enough samples for model training. (sec.3.4)

- **Evaluations and Findings.** We conduct tests on real-world vulnerability dataset to comprehensively compare and evaluate the vulnerability detection capabilities of RealVul with existing methods. Our research underscores the weakness of existing dataset and the importance of proper preprocessing. (sec.4)

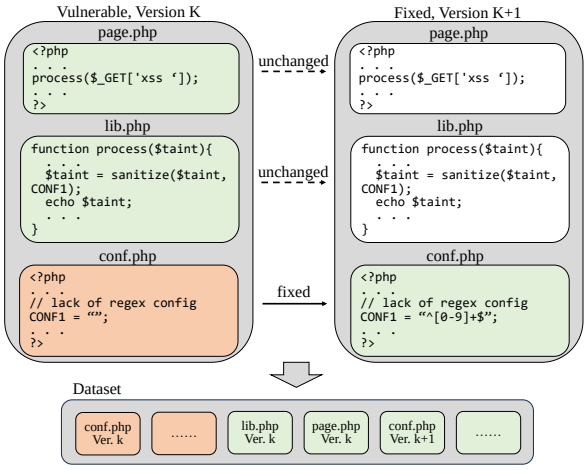


Figure 1: In the case of using vulnerability repair to build a dataset, the green part will be considered secure, and the red part will be considered vulnerable.

2 Related Works

In this section, we provide an overview of previous works related to vulnerability detection approches and the corresponding datasets. We primarily summarize the datasets and approaches used in Appendix A, as shown in Table 4 and Table 5.

2.1 Existing Datasets

Previous studies have proposed numerous vulnerability datasets, which can be broadly categorized into two types: synthetic datasets and datasets derived from real project.

Synthetic datasets are simplified and isolated, and while they contain accurate labels, they lack noise and contextual information, and fail to fully encapsulate the complexity of real-world vulnerabilities. For example, SARD (NIST, 2005) and Juliet (Okun et al., 2013) are overly simplified and do not accurately represent the vulnerabilities that may be encountered in practical applications.

To address the limitations of synthetic datasets, some researchers have suggested collecting data based on vulnerability repair. For vulnerability datasets(Zhou et al., 2019; Chakraborty et al., 2020; Fan et al., 2020; Zheng et al., 2021; Nikitopoulos et al., 2021; Chen et al., 2023) derived from real projects, the common approach is to collect vulnerabilities and their corresponding fixes. While this may seem logical, previous research(Croft et al., 2023) has indicated that this data collection method still has issues with accuracy, uniqueness, and other aspects.

For instance, consider a potential PHP vulnerability fix, as illustrated in Figure 1. The execution path of the vulnerability passes through three functions. When extracting samples, this method will split the execution path of the vulnerability into four samples based on whether the function has been fixed. During the model training process, the correlation between samples will be ignored, making it difficult for the model to identify the vulnerability based only on this dataset.

Furthermore, the automatic collection of vulnerability datasets based on vulnerability repair may introduce additional issues, such as including unknown vulnerabilities in the code, which can negatively impact model performance. In our view, vulnerability detection and vulnerability code repair are two different tasks in different stages of vulnerability management. Therefore, we need to take a new approach to extract vulnerability datasets.

2.2 Existing Approaches

Early research primarily employed deep learning models such as RNN and GNN for analysis. Token-based methods transform code into tokens for examination. μVulDeePecker(Zou et al., 2019) introduces the concept of code attention and utilizes the Building-block BLSTM network. SySeVR(Li et al., 2021) incorporates semantic information into the vulnerability syntax candidate SyVCs to generate SeVCs and tests them on models such as BRNN and BGRU.

Graph-based methods transform code into graph structures for examination. Devign(Zhou et al., 2019) and Reveal(Chakraborty et al., 2020) leverages the Code Property Graph (CPG) proposed by Yamaguchi et al.(Yamaguchi et al., 2014) to construct vulnerability prediction model. LineVD(Hin et al., 2022) utilizes Program Dependency Graph (PDG) to achieve more precise vulnerability localization. VulChecker further (Mirsky et al., 2023) employed ePDG and S2V to further capture the correlation between vulnerability codes.

With the advancements in natural language processing, models such as CodeBERT(Feng et al., 2020) have demonstrated remarkable code comprehension and generation capabilities, leading more researchers to use them for vulnerability analysis. LineVul(Fu and Tantithamthavorn, 2022) employs CodeBERT as its core and implements fine-grained vulnerability classification and localization based on the attention mechanism. DiverseVul(Chen et al., 2023) uses models like RoBERTa(Liu et al., 2019), GPT-2(Radford et al., 2019), and CodeT5(Wang et al., 2021) to analyze vulnerability detection capabilities. However, these works are overly reliant on existing datasets and lack reasonable preprocessing of vulnerability code, such as code slicing and duplicate removal. They directly analyze vulnerability code samples, resulting in unreliable analysis of unknown projects(Chen et al., 2023). Recently, the rapid development of large language models has triggered disruptive changes in related fields. It performs outstanding in code-intensive fields such as code synthesis (Wu et al., 2023; Jiang et al., 2023) and automated programming assistance (Leung and Murphy, 2023; Wei et al., 2023), making its potential in software vulnerability detection obvious.

In RealVul, we process samples reasonably by locating vulnerability triggers, code slicing, irrelevant information permutation, and removing similar samples, and use more advanced code LLM for analysis to achieve superior performance.

3 Method

This section elucidates the design rationale and the architecture of our proposed approach, RealVul. For each type of CWE, RealVul employs distinct strategies for sample selection and processing, and trains separate models for analysis. Our methodology is expounded upon from three perspectives: sample selection, data preprocessing, and model training. Figure 2 illustrates the architecture of our approach.

3.1 Vulnerability Candidate Detection

In this phase, our objective is to scrutinize potential vulnerability triggers in the code and slice the program based on these triggers. This generates code snippets that are syntactically correct and solely associated with one vulnerability trigger, thereby

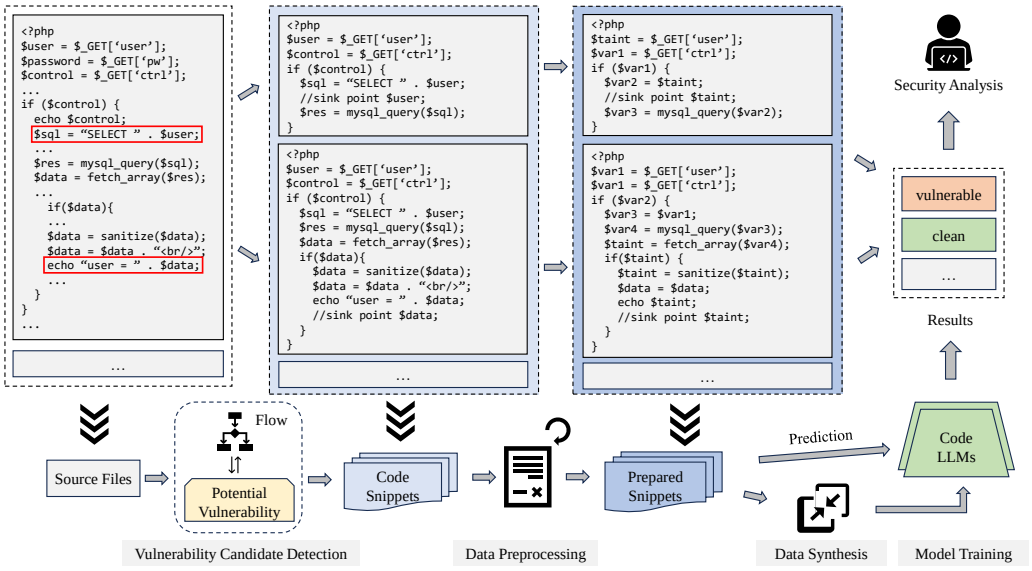


Figure 2: RealVul architecture overview.

reducing noise and ensuring a robust correlation between vulnerabilities and samples. Figure 3 depicts the process of our approach of vulnerability candidate detection.

3.1.1 Potential Vulnerability Localization

To extract samples from source files, we initially employ our domain expertise and heuristic rule matching to identify statements in the code that could potentially trigger vulnerabilities. We have detailed specific identification methods for two types of CWE vulnerabilities in Appendix B.

For the identified potential vulnerability statements, we analyze the variables used for concatenation, considering each concatenated variable as a potential vulnerability source. We then mark the current variable as a tainted variable, and this variable is deemed a potential vulnerability trigger. The analysis of potential vulnerability triggers here is predicated on our design assumption that we already have knowledge of which functions in the program are executed freely and which code could potentially lead to vulnerabilities. In practical applications, users can modify the rules to suit their needs for more accurate matching or detecting other types of vulnerabilities.

3.1.2 Program Slicing

To trim the program code, we analyze the PHP file's code to eliminate code comments, generate an Abstract Syntax Tree (AST), and extract global code, function code, and control and data flow based on the AST. We then analyze the statement where the current potential vulnerability trigger is located. Given that multiple variables in the current statement could potentially trigger the vulnerability, we replace variables other than the currently analyzed tainted variable with constants to facilitate focused analysis of a single variable. We search for potential vulnerability triggers related to data flow and control flow in the current analysis. We label the variables in these statements as relevant variables and further recursively search. Ultimately, we identify all statements related to potential vulnerability triggers. While ensuring correct syntax, we extract these code statements as samples.

If the potential vulnerability is within the function, we posit that function variables are deemed untrustworthy inside the function as they are passed in from outside the function. Therefore, we rewrite these variables in the form of global variables "$_GET", and convert the function code to global code. This enables us to standardize the different representations of function code and global code. Upon completing the vulnerability candidate detection, we use code comments to mark taint variables at potential vulnerability triggers to enhance the sample's vulnerability representation.

3.2 Data Preprocessing

In this phase, our objective is to reduce irrelevant information in the samples and ensuring suitable preprocessing of the dataset. We accomplish the preprocessing of the sample set through the following three steps.

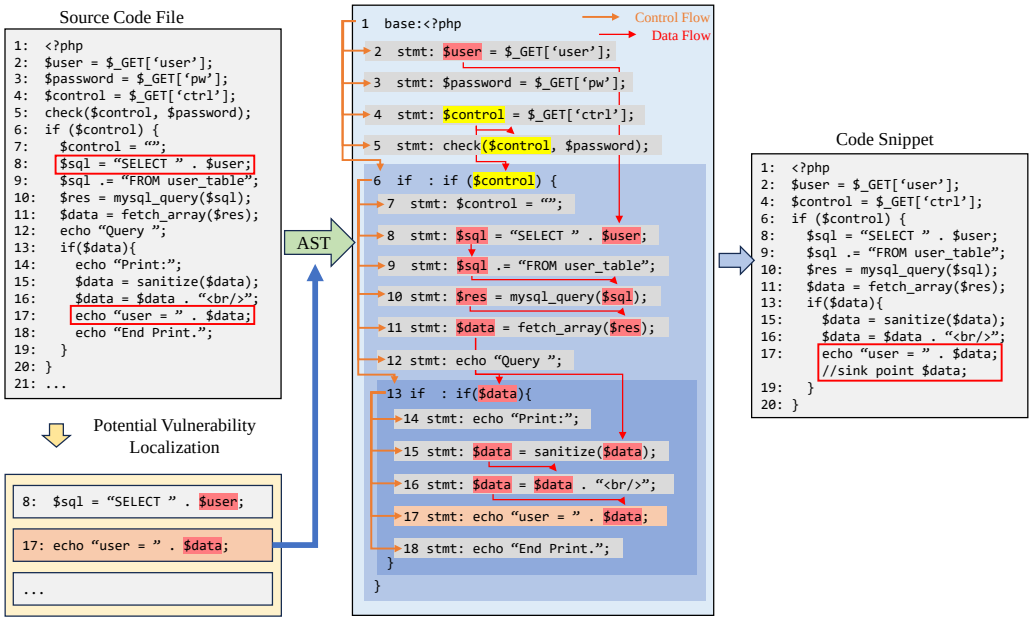


Figure 3: The process of vulnerability candidate detection from a real-world PHP project. We identify potential vulnerability triggers and analyze the data flow and control flow through the source file's AST. The obtained code snippets are our samples.

3.2.1 Labeling

Each extracted sample is labeled based on its potential to lead to specific types of vulnerabilities. Samples with and without vulnerabilities are labeled as y= {good, bad}. Given that only one tainted variable is passed into the potential vulnerability statement in the samples, the labels of the samples correspond one-to-one with the variables that could potentially trigger the vulnerability. This is what we consider as the strong correlation between the samples and vulnerability information.

3.2.2 Normalizing

We note that the program code contains some information that is not essential for vulnerability analysis. This information primarily includes constant strings and variable names. Due to the nature of web applications, the code often contains many constant strings, some of which are excessively long and do not significantly impact vulnerability analysis, such as strings of HTML statements.

To preserve semantic information as much as possible, previous research often refrained from processing this content. However, in this paper, we eliminate what we consider unnecessary semantic information through keyword detection. Our experiments (sec.4.4) demonstrate that this approach is effective.

Variable names, defined by programmers, do not have a fixed form due to varying coding habits, which could potentially affect the performance of vulnerability detection models. For vulnerability analysis, the names of variables do not indicate whether the data they contain poses a threat, rendering this information unnecessary. We standardize the code by mapping identical variables to the same values and renaming different variables (i.e., "var0", "var1"). We retain user-defined function names because they provide semantic information that reveals the function's behavior.

3.2.3 Deduplication

Following the normalization process, there may be similar samples in the sample set due to the removal of some irrelevant information and the presence of code reuse. Code duplication has been shown to negatively impact trained models(Allamanis, 2019). Ensuring the uniqueness of samples in the dataset aids the model in generalizing to the true data distribution. Based on sequence alignment analysis, we remove all space characters from the vulerability samples to assess their similarity and set a threshold based on experience to remove highly repetitive code.

3.3 Model Training

Upon the completion of sample collection and processing, we fine-tune the pre-trained code LLMs to classify the previously collected and processed samples. These preprocessed code samples are

inputted into code LLMs, with the model's task being to ascertain the presence of vulnerabilities in the samples through sequence classification. We employ the Low Rank Adaptive (LoRa) technique (Hu et al., 2021) to fine-tune the Query and Key in the self-attention layers of the LLM. Given the varying performance of different types of CWEs, we train models for each CWE type separately to achieve specific vulnerability detection for a particular type.

3.4 Data Synthesis

While our aim is to extract vulnerability samples through code statements that may trigger vulnerabilities, there is no existing dataset that fulfills our requirements. This is due to the fact that the vulnerability dataset of real projects originates from vulnerability repair, while synthetic datasets such as SARD do not align with the code in real-world projects. Given that existing datasets cannot meet our research needs, we designed vulnerability candidate detection and preprocessing methods to obtain datasets suitable for model training. However, manual labeling method (3.2.1) limits the amount of vulnerability samples, and we need to build a large-scale dataset for model fine-tuning. Therefore, the data synthesis method introduced in this section is crucial.

Referring to data synthesis methods from existing research(Mirsky et al., 2023), which procures new vulnerability samples by inserting pure vulnerability samples into projects devoid of vulnerabilities, we extend this method to generate PHP source code samples that meets our requirements. We select samples with shorter data stream lengths and less complex conditional branches, and insert them into functions of real projects. These functions are then sliced and preprocessed to finally get our synthetic dataset. Appendix C describes the detailed process of our data synthesis.

4 Evaluation

This section outlines the experimental details, encompassing the experiment setup and datasets. Then we fine-tune Code LLM through data obtained from synthesis and conduct a comprehensive comparison of our method with existing methodologies, thereby validating the enhancement of our method's effectiveness and generalization capability.

4.1 Experiments and Datasets

4.1.1 Experiments

We execute extensive experiments to validate the performance of RealVul, considering two scenarios: model prediction code and model training code derive from identical and different PHP projects. We design three related experiments accordingly.

EXP1: Effectiveness. For the first scenario, we do not distinguish the projects where the samples in the training, validation, and test sets come from. As a baseline, We compare the performance of RealVul and LLMs fine-tuned by vulnerability-repair-based datasets. These dataset will be randomly divided into training, validation and test sets.

EXP2: Generalization. For the second scenario, We require that the data used for testing is unknown to the fine-tuned LLMs. This means that the training set, validation set and test set are as unrelated as possible in terms of data sources. For the dataset of baseline method, we impose the same requirements, ensuring the these three sets are sourced from different projects.

To further demonstrate the real-world application capabilities of RealVul, we conduct a comparison of RealVul with two common PHP SAST tools, RIPS(RIP) and Fortify SCA(for), in terms of their function-level analysis capabilities.

EXP3: Ablation Study. Normalization and model training are two crucial component of our sample processing. To demonstrate that normalization generally enhances model performance, we conduct corresponding experiments on CWE-79 vulnerabilities. We use non-normalized datasets for training and testing, and compare the results with the first two experiments. We also compare RealVul with in-context learning approaches to demonstrate the necessity of fine-tuning. We use both Zero-shot and Few-shot prompts.

In line with the evaluation metrics of existing researches(Chakraborty et al., 2020; Fu and Tantithamthavorn, 2022; Chen et al., 2023), we employ four metrics: accuracy, recall, precision, and F1 score to thoroughly evaluate our experimental results. During the sampling phase, we implement AST generation of PHP code using the PHPLy (php). We primarily use CodeT5(Wang et al., 2021), CodeT5p(Wang et al., 2023b), CodeLlama(Roziere et al., 2023), and the latest StarCoder2(Lozhkov et al., 2024) to demonstrate the effectiveness of RealVul, including five models: CodeT5-base, CodeT5p-770m, CodeLlama-7b,

Methods		CWE-79					CWE-89				
		Acc	Rec	Pre	F1	ΔF1	Acc	Rec	Pre	F1	ΔF1
RealVul	CodeLlama-7b	**91.47**	**87.96**	**79.80**	**83.68**	+51.3	92.35	78.13	79.37	78.74	+73.6
	StarCoder2-7b	89.74	86.50	75.71	80.75	+50.5	90.08	**84.38**	68.35	75.52	+57.3
	StarCoder2-3b	88.48	88.69	71.68	79.28	+29.3	92.63	78.13	**80.65**	**79.37**	+73.5
	CodeT5p-770m	89.02	83.58	75.08	79.10	+53.7	88.39	76.56	65.33	70.50	+37.2
	CodeT5-base	89.02	84.67	74.60	79.32	+46.0	79.89	82.81	46.90	59.89	+31.3
Baseline	CodeLlama-7b	86.51	26.83	40.74	32.35	-	89.52	3.85	7.69	5.13	-
	StarCoder2-7b	86.51	24.39	40.00	30.30	-	89.80	15.38	22.22	18.18	-
	StarCoder2-3b	88.27	48.78	51.28	50.00	-	90.93	3.85	12.50	5.88	-
	CodeT5p-770m	86.22	19.51	36.36	25.40	-	**93.20**	23.08	60.00	33.33	-
	CodeT5-base	87.10	26.83	44.00	33.33	-	92.91	19.23	55.56	28.57	-

Table 1: Evaluation results on Random Samples. ΔF1 is the difference between the F1 scores of RealVul and Baseline methods.

Methods		CWE-79					CWE-89				
		Acc	Rec	Pre	F1	ΔF1	Acc	Rec	Pre	F1	ΔF1
RealVul	CodeLlama-7b	81.71	75.36	63.41	68.87	+43.2	76.19	**100.00**	45.95	62.96	+23.0
	StarCoder2-7b	77.43	63.77	57.14	60.27	+56.9	86.90	97.06	**61.11**	**75.00**	+46.4
	StarCoder2-3b	79.76	75.36	59.77	66.67	+41.4	66.67	97.06	37.50	54.10	+28.7
	CodeT5p-770m	82.88	**73.91**	**66.23**	**69.86**	+19.9	86.31	97.06	60.00	74.16	+31.5
	CodeT5-base	74.32	71.01	51.58	59.76	+1.1	70.24	97.06	40.24	56.89	+18.4
Baseline	CodeLlama-7b	89.38	17.86	45.45	25.64	-	**87.23**	37.84	42.42	40.00	-
	StarCoder2-7b	89.74	1.79	33.33	3.40	-	86.32	24.32	34.62	28.57	-
	StarCoder2-3b	89.19	17.86	43.48	25.32	-	85.71	21.62	30.77	25.40	-
	CodeT5p-770m	89.01	53.57	46.88	50.00	-	84.50	51.35	36.53	42.70	-
	CodeT5-base	**89.93**	69.64	50.65	58.65	-	85.41	40.54	36.58	38.46	-

Table 2: Evaluation results on Unseen Projects. ΔF1 is the difference between the F1 scores of RealVul and Baseline methods.

StarCoder2-3b, and StarCoder2-7b. In the Ablation Study on model fine-tuning, we utilized the in-context learning approaches to directly evaluate GPT-4, as well as other SOTA open-source LLMs such as Mistral-7B, Llama3-8B, and CodeLlama-7B. We used both zero-shot and few-shot prompts. In the few-shot prompts, we provided two demonstration examples to help the LLMs understand the context of the task. The Appendix D provides detailed information about models and evaluation metrics.

4.1.2 Datasets

We collect samples from the CrossVul dataset(Nikitopoulos et al., 2021) for training and testing models of RealVul and baseline method. The CrossVul dataset provides PHP files pre and post vulnerability repair, which allows us to collect the datasets from the same data source in different ways. We use the RealVul framework to obtain real-world vulnerability datasets, denoted as D_{real}. Leveraging our data synthesis algorithm, we synthesize a large-scale dataset D_{syn} from D_{real} and the SARD dataset(NIST, 2005). For the baseline method, we obtaine another dataset by comparing the code differences pre and post vulnerability repair, denoted as D_{rep}.

To evaluate RealVul, we split the D_{syn} as the training and validation sets, and we use D_{real} as the test set. For the baseline method, we split the D_{syn} as the training, validation and test sets. In **EXP1**, we split the dataset through random sampling. But in **EXP2**, we strictly split the datasets based on the source projects. We stipulate that the code samples in the test set can't be used for synthesizing training and validation sets, and the samples used for synthesizing validation sets could not be used for synthesizing training sets. In **EXP3**, we use non-normalized datasets D_{real}* and D_{syn}* for training and testing, and we use D_{real} to evaluate the in-context learning approaches. We provide more information in Appendix D, including statistics and properties of our datasets.

4.2 Effectiveness

Table 1 presents the evaluation outcomes of two vulnerabilities, CWE-79 (XSS) and CWE-89 (SQLI), utilizing the same data source on our test set D_{real}. Based on these results, we can infer the following:

Despite our training data being algorithmically synthesized, the evaluation outcomes of RealVul exhibit commendable performance across four metrics. Even for the CWE-89 type, which has a smaller real data sample size, the evaluation outcomes remain relatively stable. This suggests that our synthesized dataset aligns well with the real dataset, and training with synthesized data can effectively evaluate code samples in real environments. Due to the limited data volume in CWE-89, its overall F1 score performance is not as stable as that of CWE-79, indicating potential for further enhancement of our method's analytical capability by increasing the number of real sample data.

Comparing with the baseline method further reveals that our RealVul method generally outperforms the baseline method, with RealVul combined with CodeLlama-7b and StarCoder2-3b delivering the best performance in the CWE-79 and CWE-89 tasks, particularly in terms of F1 score. In contrast, the F1 score of the vulnerability repair-based sampling method does not exceed 50%. This suggests that our sampling and processing techniques enable our code to better represent vulnerability feature information, thereby enhancing the LLM code's performance in vulnerability detection.

4.3 Generalization

Table 2 displays the evaluation outcomes on test sets from different data sources. These results substantiate that our RealVul method more effectively encapsulates vulnerability-related information in the code and achieves superior generalization performance.

In our training data, the proportion of vulnerability samples is relatively small, reflecting the uneven distribution of vulnerability samples in real environments and imposing higher demands on the analytical method's capability. Therefore, although our method may slightly lack accuracy compared to the baseline, our F1 score significantly surpasses the baseline. The baseline's input is complete function code or top-level code, which increases the model's analytical difficulty compared to samples obtained by our method.

Methods		CWE-79			CWE-89		
		TP	FP	Times (s)	TP	FP	Times (s)
RealVul	CodeLlama-7b	40	14	152	**30**	17	147
	StarCoder2-7b	34	24	130	29	22	151
	StarCoder2-3b	38	11	56	29	9	64
	CodeT5p-770m	39	15	23	29	20	32
	CodeT5-base	32	16	7	29	12	10
RIPS		**43**	30	<1	3	3	<1
Fortify SCA		40	**8**	30	1	**0**	28

Table 3: Comparison of RealVul and two SAST tools. We also provide the time required for the evaluation.

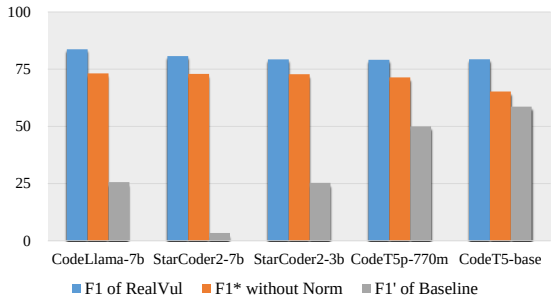
Additionally, we observe that the model's parameter count has minimal impact on its vulnerability detection capability. Even smaller models like Codet5 and Codet5p possess sufficient analytical capabilities to accomplish the analysis task. This suggests that our method, by vulnerability candidate detection and preprocessing, reduces individual sample code length and emphasizes potential vulnerability trigger-related information, thereby reducing the model's analytical capability requirements.

We also present the comparative results of RealVul and the two traditional SAST tools in Table 3. From the results, our method performs slightly worse than static tools on CWE-79. However, our method obviously outperforms static tools on CWE-89. This is because we match the behavior of concatenating SQL statements rather than the functions executing SQL statements when selecting potential vulnerability points for SQL injection vulnerabilities. This allows us to more comprehensively identify SQL vulnerabilities.

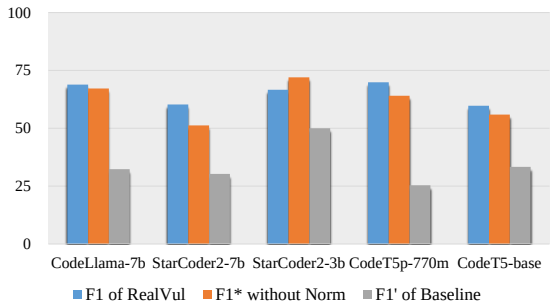
In traditional methods, the improvement of vulnerability detection requires the continuous accumulation of rules, which increases the time necessary for analysis. It is worth noting that while SAST tools primarily rely on the CPU for computation during runtime, the part of our method that applies the CodeT5 series models takes less evaluation time than SAST tools, and the accuracy is fairly close to that of traditional SAST tools. In Appendix E, we provide further explanation through case study.

4.4 Ablation Study

The ablation study results of normalization, presented in Figure 4, clearly show that although StarCoder2-3b experiences a certain decrease in F1 scores when tested on unseen projects, normal-



(a) Test on Random Samples



(b) Test on Unseen Projects

Figure 4: Comparison of ablation study results with the visualization of results from the first two experiments.

ization processing is necessary in most cases, with the maximum F1 score difference reaching 14.06%. This suggests that appropriately reducing irrelevant semantic information may lead to better results in PHP vulnerability detection tasks. What's more, normalizing the function name might yield better results. However, to retain the function's necessary information, it is essential to construct a function call graph and analyze its functionality, which necessitates further development of an analysis system.

Although the absence of normalization processing can lead to a decrease in evaluation outcomes, our sampling method still outperforms Baseline in previous experiments, indicating its superiority over vulnerability repair-based methods. We present all the evaluation outcomes of this ablation study in Appendix E.

The evaluation results of ablation study on model fine-tuning are shown in Table 9 in Appendix E. It is obvious that there is a significant performance gap between the in-context learning approaches and RealVul, which shows the contribution of our RealVul. This also confirms the conclusion of existing research(Steenhoek et al., 2024) that the models lack the ability to directly use in-context learning to understand software vulnerabilities, thus fine-tuning is necessary.

5 Conclusion

In this paper, we concentrate on PHP web vulnerability detection utilizing code LLMs. To enhance detection proficiency, we identifies potential vulnerability triggers, analyzes control flow and data flow, and eliminates unnecessary semantic information to obtain samples robustly correlated with vulnerability information. Based on the improved data synthesis method, we extensively synthesize new vulnerability samples, thereby alleviating the challenge of insufficient vulnerability dataset of PHP. We carry out extensive experiments, comparing our method with existing techniques using samples derived from real-world projects. The experimental outcomes indicate that our method exhibits significantly superior capabilities in comparison to existing techniques.

Limitations

We acknowledge three potential limitations in our study that warrant further exploration in future research: (i) During the normalization process, we preserve user-defined function names. We posit that integrating function call analysis, standardizing function name representation, and supplementing code comments with functional information could potentially enhance the effectiveness of our approach. (ii) We fine-tune our model specifically for each type of CWE vulnerability to augment detection capabilities. This approach incurs substantial overhead and the performance of a unified multi-classification model merits investigation. (iii) At present, there is a dearth of effective vulnerability sample labeling methods, leading us to resort to manual labeling of samples and data synthesis to compensate for the lack of sufficient data volume. Consequently, the efficacy of our dataset could be further improved. (iiii) We adopted a heuristic rule-based approach to identify potential vulnerability triggering statements, and these rule bases still need to be extended or modified in our framework to adapt to new vulnerability patterns or updated programming practices.

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References

checkmarx. https://checkmarx.com/. Accessed: May 8, 2024.

Codeql. https://codeql.github.com/. Accessed: July 27, 2024.

fortify. https://www.microfocus.com/en-us/cyberres/application-security. Accessed: May 8, 2024.

Github. https://github.com/. Accessed: May 8, 2024.

phply. https://github.com/viraptor/phply. Accessed: May 8, 2024.

Rips. https://rips-scanner.sourceforge.net/. Accessed: May 8, 2024.

Sonarqube. https://www.sonarsource.com/. Accessed: May 8, 2024.

Miltiadis Allamanis. 2019. The adverse effects of code duplication in machine learning models of code. In *Proceedings of the 2019 ACM SIGPLAN International Symposium on New Ideas, New Paradigms, and Reflections on Programming and Software*, pages 143–153.

Saikat Chakraborty, Rahul Krishna, Yangruibo Ding, and Baishakhi Ray. 2020. Deep learning based vulnerability detection: Are we there yet? *IEEE Transactions on Software Engineering*, 48(9):3280–3296.

Yizheng Chen, Zhoujie Ding, Lamya Alowain, Xinyun Chen, and David Wagner. 2023. Diversevul: A new vulnerable source code dataset for deep learning based vulnerability detection. In *Proceedings of the 26th International Symposium on Research in Attacks, Intrusions and Defenses*, pages 654–668.

Roland Croft, M Ali Babar, and M Mehdi Kholoosi. 2023. Data quality for software vulnerability datasets. In *2023 IEEE/ACM 45th International Conference on Software Engineering (ICSE)*, pages 121–133. IEEE.

Jiahao Fan, Yi Li, Shaohua Wang, and Tien N Nguyen. 2020. Ac/c++ code vulnerability dataset with code changes and cve summaries. In *Proceedings of the 17th International Conference on Mining Software Repositories*, pages 508–512.

Zhangyin Feng, Daya Guo, Duyu Tang, Nan Duan, Xiaocheng Feng, Ming Gong, Linjun Shou, Bing Qin, Ting Liu, Daxin Jiang, et al. 2020. Codebert: A pre-trained model for programming and natural languages. *arXiv preprint arXiv:2002.08155*.

Michael Fu and Chakkrit Tantithamthavorn. 2022. Linevul: A transformer-based line-level vulnerability prediction. In *Proceedings of the 19th International Conference on Mining Software Repositories*, pages 608–620.

David Hin, Andrey Kan, Huaming Chen, and M Ali Babar. 2022. Linevd: Statement-level vulnerability detection using graph neural networks. In *Proceedings of the 19th international conference on mining software repositories*, pages 596–607.

Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. 2021. Lora: Low-rank adaptation of large language models. *arXiv preprint arXiv:2106.09685*.

Nan Jiang, Kevin Liu, Thibaud Lutellier, and Lin Tan. 2023. Impact of code language models on automated program repair. In *2023 IEEE/ACM 45th International Conference on Software Engineering (ICSE)*, pages 1430–1442. IEEE.

Mira Leung and Gail Murphy. 2023. On automated assistants for software development: The role of llms. In *2023 38th IEEE/ACM International Conference on Automated Software Engineering (ASE)*, pages 1737–1741. IEEE.

Zhen Li, Deqing Zou, Shouhuai Xu, Hai Jin, Yawei Zhu, and Zhaoxuan Chen. 2021. Sysevr: A framework for using deep learning to detect software vulnerabilities. *IEEE Transactions on Dependable and Secure Computing*, 19(4):2244–2258.

Zhen Li, Deqing Zou, Shouhuai Xu, Xinyu Ou, Hai Jin, Sujuan Wang, Zhijun Deng, and Yuyi Zhong. 2018. Vuldeepecker: A deep learning-based system for vulnerability detection. *arXiv preprint arXiv:1801.01681*.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*.

Anton Lozhkov, Raymond Li, Loubna Ben Allal, Federico Cassano, Joel Lamy-Poirier, Nouamane Tazi, Ao Tang, Dmytro Pykhtar, Jiawei Liu, Yuxiang Wei, et al. 2024. Starcoder 2 and the stack v2: The next generation. *arXiv preprint arXiv:2402.19173*.

Yisroel Mirsky, George Macon, Michael Brown, Carter Yagemann, Matthew Pruett, Evan Downing, Sukarno Mertoguno, and Wenke Lee. 2023. {VulChecker}: Graph-based vulnerability localization in source code. In *32nd USENIX Security Symposium (USENIX Security 23)*, pages 6557–6574.

MITRE. Cve. https://cve.mitre.org/. Accessed: May 8, 2024.

Georgios Nikitopoulos, Konstantina Dritsa, Panos Louridas, and Dimitris Mitropoulos. 2021. Crossvul: a cross-language vulnerability dataset with commit data. In *Proceedings of the 29th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, pages 1565–1569.

NIST. 2005. Nist software assurance reference dataset. Accessed: 2024-05-17.

Vadim Okun, Aurelien Delaitre, Paul E Black, et al. 2013. Report on the static analysis tool exposition (sate) iv. *NIST Special Publication*, 500:297.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9.

Baptiste Roziere, Jonas Gehring, Fabian Gloeckle, Sten Sootla, Itai Gat, Xiaoqing Ellen Tan, Yossi Adi, Jingyu Liu, Tal Remez, Jérémy Rapin, et al. 2023. Code llama: Open foundation models for code. *arXiv preprint arXiv:2308.12950*.

Calif. Sausalito. 2023 cybersecurity almanac: 100 facts, figures, predictions, and statistics. https://cybersecurityventures.com/cybersecurity-almanac-2023/. Accessed: May 8, 2024.

Benjamin Steenhoek, Md Mahbubur Rahman, Monoshi Kumar Roy, Mirza Sanjida Alam, Earl T Barr, and Wei Le. 2024. A comprehensive study of the capabilities of large language models for vulnerability detection. *arXiv preprint arXiv:2403.17218*.

Yuqiang Sun, Daoyuan Wu, Yue Xue, Han Liu, Wei Ma, Lyuye Zhang, Miaolei Shi, and Yang Liu. 2024. Llm4vuln: A unified evaluation framework for decoupling and enhancing llms' vulnerability reasoning. *arXiv preprint arXiv:2401.16185*.

W3Techs. Usage statistics of server-side programming languages for websites. https://w3techs.com/technologies/overview/programming_language. Accessed: May 8, 2024.

Huanting Wang, Guixin Ye, Zhanyong Tang, Shin Hwei Tan, Songfang Huang, Dingyi Fang, Yansong Feng, Lizhong Bian, and Zheng Wang. 2020. Combining graph-based learning with automated data collection for code vulnerability detection. *IEEE Transactions on Information Forensics and Security*, 16:1943–1958.

Jin Wang, Zishan Huang, Hengli Liu, Nianyi Yang, and Yinhao Xiao. 2023a. Defecthunter: A novel llm-driven boosted-conformer-based code vulnerability detection mechanism. *arXiv preprint arXiv:2309.15324*.

Yue Wang, Hung Le, Akhilesh Deepak Gotmare, Nghi DQ Bui, Junnan Li, and Steven CH Hoi. 2023b. Codet5+: Open code large language models for code understanding and generation. *arXiv preprint arXiv:2305.07922*.

Yue Wang, Weishi Wang, Shafiq Joty, and Steven CH Hoi. 2021. Codet5: Identifier-aware unified pre-trained encoder-decoder models for code understanding and generation. *arXiv preprint arXiv:2109.00859*.

Yuxiang Wei, Chunqiu Steven Xia, and Lingming Zhang. 2023. Copiloting the copilots: Fusing large language models with completion engines for automated program repair. In *Proceedings of the 31st ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, pages 172–184.

Yi Wu, Nan Jiang, Hung Viet Pham, Thibaud Lutellier, Jordan Davis, Lin Tan, Petr Babkin, and Sameena Shah. 2023. How effective are neural networks for fixing security vulnerabilities. In *Proceedings of the 32nd ACM SIGSOFT International Symposium on Software Testing and Analysis*, pages 1282–1294.

Fabian Yamaguchi, Nico Golde, Daniel Arp, and Konrad Rieck. 2014. Modeling and discovering vulnerabilities with code property graphs. In *2014 IEEE symposium on security and privacy*, pages 590–604. IEEE.

Yunhui Zheng, Saurabh Pujar, Burn Lewis, Luca Buratti, Edward Epstein, Bo Yang, Jim Laredo, Alessandro Morari, and Zhong Su. 2021. D2a: A dataset built for ai-based vulnerability detection methods using differential analysis. In *Proceedings of the ACM/IEEE 43rd International Conference on Software Engineering: Software Engineering in Practice*, ICSE-SEIP '21, New York, NY, USA. Association for Computing Machinery.

Yaqin Zhou, Shangqing Liu, Jingkai Siow, Xiaoning Du, and Yang Liu. 2019. Devign: Effective vulnerability identification by learning comprehensive program semantics via graph neural networks. *Advances in neural information processing systems*, 32.

Deqing Zou, Sujuan Wang, Shouhuai Xu, Zhen Li, and Hai Jin. 2019. μ vuldeepecker: A deep learning-based system for multiclass vulnerability detection. *IEEE Transactions on Dependable and Secure Computing*, 18(5):2224–2236.

A Related Works

The statistical data of existing vulnerability detection datasets and research methods are shown in Tables 4 and 5.

B Vulnerability Candidate Detection

Different methods are needed to identify potential vulnerability triggers for different types of vulnerabilities. For XSS vulnerabilities (CWE-79), the potential statement is *echo*, *print* and other output statements.

However, searching for functions that execute SQL statements through matching as potential vulnerability points is highly inaccurate. On the one hand, many PHP projects do not use PHP's native SQL execution functions, and they often use self written SQL execution functions or some PHP

Datasets	Size	Type	Language
SARD(NIST, 2005)	450K	Synthetic	C/C++/Java/PHP/C#
SATE IV Juliet(Okun et al., 2013)	253K	Synthetic	C/C++/Java
Devign(Zhou et al., 2019)	23K	Real	C
Reveal(Chakraborty et al., 2020)	18K	Real	C
Big-Vul(Fan et al., 2020)	188K	Real	C/C++
D2A(Zheng et al., 2021)	1.3M	Real	C/C++
CrossVul(Nikitopoulos et al., 2021)	27K	Real	C/C++/Java/PHP/...
DiverseVul(Chen et al., 2023)	349K	Real	C/C++

Table 4: Overview of Existing Vulnerability Datasets

Approaches	Input	Model	Language
VulDeePecker(Li et al., 2018)	Token (Code Gadget)	Bi-LSTM	C/C++
μVulDeePecker(Zou et al., 2019)	Token (Code Gadget)	B-BLSTM	C/C++
Devign(Zhou et al., 2019)	Graph (CPG)	GCN	C
Reveal(Chakraborty et al., 2020)	Graph (CPG)	GGNN	C
SySeVR(Li et al., 2021)	Token (SeVC)	BRNN, BGRU	C/C++
LineVul (Fu and Tantithamthavorn, 2022)	Token (Code)	CodeBert	C/C++
LineVD(Hin et al., 2022)	Graph (PDG)	GCN, GAT	C/C++
VulChecker(Mirsky et al., 2023)	Graph (ePDG)	S2V, DNN	C/C++
DiverseVul(Chen et al., 2023)	Token (Code)	RoBERTa, GPT-2, CodeT5	C/C++
RealVul(Ours)	Token (Processed Code)	CodeT5, CodeT5+, CodeLlama, StarCoder2	PHP

Table 5: Overview of Existing Vulnerability Detection Approches

framework functions, which makes it difficult to match all potential vulnerability points. On the other hand, the matched SQL execution function cannot determine whether a filter for SQL injection vulnerabilities is built-in. In practice, SQL statements often need to be concatenated with variables before execution, so we match statements that directly concatenate SQL statements with variables as potential vulnerability trigger statements.

C Data Synthesis

Algorithm 1 demonstrates our data synthesis method. By analyzing the AST of the samples, we use the code corresponding to the top-level AST node as the basic unit for inserting into the clean project code. Subsequently, we analyze the control flow of the project code, randomly select a control flow path, and remove potential code trigger statements to obtain clean project code. After T rounds of synthesis, syntax checking of the code, program slicing, and preprocessing as described in sections 3.1 and 3.2, we ultimately obtain our synthesized dataset.

D Experiments Setup

Model Configuration. Table 6 presents an overview of the Code LLMs we apply in our paper. We use cross entropy as the loss function and deploy LLMs on four NVIDIA-V100 GPU with 32GB of memory for training and testing to demonstrate the effectiveness of RealVul. We adopt Adam optimizer in fp16 precision, 32 global batch size. We set the training epoch to 2 and 3 for test on random samples and test on unseen projects. We add an additional epoch for samples of CWE-89 because its data is small.

Datasets. Table 8 presents an overview of the dataset utilized in our paper. The sample size derived from our methodology is comparatively smaller than that obtained through vulnerability repair, primarily due to the constraints of our manual labeling process. Furthermore, we pinpoint potential triggers for CWE-89 type vulnerabilities by scrutinizing instances where variables are amalgamated into SQL statements within the code. Despite drawing from the vulnerability dataset, such SQL concatenation instances are relatively infre-

Code LLM	Size	Release Time	Base Model	Publisher	License
CodeT5-base	220M	Sep-2021	T5	Salesforce	Open-source
CodeT5p-770m	770M	May-2023	T5	Salesforce	Open-source
CodeLlama-7b	7B	Jun-2023	Llama2-7b	Meta AI	Open-source
StarCoder2-3b	3B	Feb-2024	-	BigCode	Open-source
StarCoder2-7b	7B	Feb-2024	-	BigCode	Open-source
Llama3-8b-instruct	8B	apr-2024	-	Meta AI	Open-source
Mistral-7b-instruct-v0.3	7B	Dec-2023	Mistral-7b	Mistral AI	Open-source
GPT-4	-	Mar-2023	-	OpenAI	Closed-source

Table 6: Detail information of Models we apply in this paper.

Algorithm 1 Data Synthesis

Input: Existing pure sample set S_{raw}, projects' global code and function code set C_{proj} and synthesis times T for each sample,
Output: Synthesis samples set S_{syn} obtained through synthesis.
$S_{syn} \leftarrow \emptyset$
for each $s_{raw} \in S_{raw}$ **do**
  $C_{raw} \leftarrow$ code list of Top-level AST nodes in s_{raw}
  for each $c_{proj} \in C_{proj}$ **do**
    for i in range T **do**
      $c_p \leftarrow$ code of random path in the control flow of c_{proj}
      $c_p \leftarrow$ **remove_vuln_triggers**(c_p)
      $c_{syn} \leftarrow$ Randomly insert C_{raw} into c_p
      if syntax_check(c_{syn}) **then**
        $s_{syn} \leftarrow$**slicing_and_preprocessing**(c_{syn})
        $S_{syn} \leftarrow S_{syn} \cup \{s_{syn}\}$
      end if
    end for
  end for
end for

(a): Test on Random Samples

Code LLM	Metrics			
	Acc	Rec	Pre	F1
CodeLlama-7b	83.75	89.05	62.09	**73.16**
StarCoder2-7b	83.30	**90.51**	61.08	72.94
StarCoder2-3b	83.48	89.05	61.62	72.83
CodeT5p-770m	**84.66**	77.01	**66.56**	71.40
CodeT5-base	82.03	67.88	62.83	65.26

(b): Test on Unseen Projects

Code LLM	Metrics			
	Acc	Rec	Pre	F1
CodeLlama-7b	**84.04**	60.87	**75.00**	67.20
StarCoder2-7b	77.04	44.93	59.62	51.24
StarCoder2-3b	80.93	**91.30**	59.43	**72.00**
CodeT5p-770m	74.71	84.05	51.78	64.08
CodeT5-base	75.48	57.97	54.05	55.94

Table 7: Evaluation results of Ablation Study on normalization.

quent in comparison to "echo" and "print" statements, leading to a reduced collection of CWE-89 vulnerability samples. To counteract this issue, we amplified the frequency of single sample synthesis (T) during the data synthesis process, resulting in synthesized samples constituting approximately 30% of the total sample size. This strategy has somewhat alleviated the problem.

Our datasets are at the snippet level, and the average LoC for the XSS and SQL vulnerability datasets are 13.07 and 22.06 lines, respectively. Compared with function-level datasets, the advantages of our snippet-level dataset are fine-grained detection, simple labeling, more samples, high training efficiency, and strong sample independence. However, the contextual information provided by ours is relatively limited compared to function-level and project-level.

Evaluation Metrics. We use the following evaluation metrics:

- Accuracy indicates the overall correctness: $Acc = \frac{TP+TN}{TP+FP+FN+TN}$.
- Precision indicates the correct positive predictions part: $Pre = \frac{TP}{TP+FP}$.
- Recall calculates the correctly recalled positive examples part: $Rec = \frac{TP}{TP+FN}$.
- F1 is the harmonic mean of Precision and Recall: $F1 = 2 \cdot \frac{Pre \cdot Rec}{Pre+Rec}$. We mainly use F1 to decide the best performing model as it provides a balanced evaluation of the model's performance in terms of both Precision and Recall.

CWE	# Projects	# by Fix (D_{rep})		# RealVul (D_{real})		# for Synthesis		# Synthesis (D_{syn})	
		Total	Vuln	Total	Vuln	Total	SARD	Total	Vuln
CWE-79	154	6818	815	1102	274	1417	315	33255	12040
CWE-89	50	3525	303	353	64	543	190	14116	4237
Total	180	10343	1118	1455	338	1960	505	47371	16277

Table 8: Statistics of the dataset we used. We list the number of samples obtained through vulnerability repair, samples obtained through RealVul, samples used for data synthesis, and samples obtained through synthesis.

Methods		CWE-79				CWE-89			
		Acc	Rec	Pre	F1	Acc	Rec	Pre	F1
RealVul	CodeLlama-7b	91.47	87.96	79.80	**83.68**	92.35	78.13	79.37	**78.74**
zero-shot	CodeLlama-7b	24.86	100.00	24.86	39.82	18.18	100.00	18.18	30.77
	Llama3-8b	24.86	100.00	24.86	39.82	18.13	100.00	18.13	30.69
	Mistral-7b	24.01	100.00	24.01	38.72	17.69	100.00	17.09	29.19
	GPT-4	27.58	100.00	25.56	40.71	18.69	100.00	18.23	30.84
few-shot	CodeLlama-7b	24.58	97.36	21.63	35.40	10.81	100.00	10.20	18.52
	Llama3-8b	25.17	100.00	25.17	40.22	15.04	100.00	15.04	26.15
	Mistral-7b	33.48	97.44	26.88	42.14	24.36	89.06	17.98	29.92
	GPT-4	59.50	96.61	41.91	**58.46**	40.79	98.43	23.24	**37.61**

Table 9: Evaluation results of Ablation Study on model fine-tuning.

E Experiment Results

Case Study. We illustrate two sample cases in the Figure 5. In practical projects, there may exist longer top-level or function codes. It can be observed that compared to the original samples, our samples are shorter, contain fewer irrelevant details and maintain correct syntax. This enables the Code LLMs to more easily perform vulnerability detection tasks. Additionally, as the function code shown in the Figure 5(b), triggering functions in CWE-89 vulnerabilities are difficult to identify through traditional rules. That's why our potential vulnerability localization method significantly outperforms SAST tools in CWE-89 vulnerability detection.

Ablation Study. The detailed evaluation results of ablation study on normalization and model fine-tuning are shown in the Table 7 and Table 9.

```
function cfdef_input_list(array $p_field_def, $p_custom_field_value,
$p_required = ''){
  $t_values = explode( '|',
custom_field_prepare_possible_values($p_field_def['possible_values']));
  $t_list_size = $t_possible_values_count = count( $t_values );

  if( $t_possible_values_count > 5 ) {
    $t_list_size = 5;
    }

  if( $p_field_def['type'] == CUSTOM_FIELD_TYPE_ENUM ) {
    $t_list_size = 0;
  }

  if( $p_field_def['type'] == CUSTOM_FIELD_TYPE_MULTILIST ) {
    echo ...;
  } else {
    echo ...;
  }

  $t_selected_values = explode( '|', $p_custom_field_value );
  foreach($t_values as $t_option){
    if( in_array( $t_option, $t_selected_values, true ) ){
      echo '<option value="'.string_attribute($t_option).
'" selected="selected"> '.string_display_line($t_option).'</option>';
    } else {
      echo '<option value="'.string_attribute($t_option).
'">' . string_display_line($t_option) . '</option>';
    }
  }
  echo '</select>';
}
```

```
<?php
// controlable parameters:
$var3 = $_GET['input0'];
$var1 = $_GET['input1'];

// php code:
$var4 = explode('|',
custom_field_prepare_possible_values($var3['possible_values']));
$var2 = explode('|', $var1);
foreach( $var4 as $taint ) {
  if( in_array($taint, $var2, true ) ) {
    echo  string_attribute($taint) . string_display_line($taint) ;
    //sink point: $taint;
  }
}
```

(a) CWE-79 Case

```
static function prepopulate_versionnumber_cache($class, $stage,
$idList = null) {

  $filter = "";

  if($idList) {
    foreach($idList as $id)
      if(!is_numeric($id))
        user_error("Bad ID ... : " . $id, E_USER_ERROR);
      $filter = "WHERE \"ID\" IN(" .implode(", ", $idList).")";
  }

    $baseClass = ClassInfo::baseDataClass($class);
    $stageTable = ($stage == 'Stage') ? $baseClass :
"{$baseClass}_{$stage}";

    $versions = DB::query("SELECT \"ID\", \"Version\" FROM
\"$stageTable\" $filter")->map();

    foreach($versions as $id => $version) {
       self::$cache_versionnumber[$baseClass][$stage][$id] =
$version;
    }
}
```

```
<?php
// controlable parameters:
$var2 = $_GET['input0'];
$var3 = $_GET['input1'];

// php code:
$var1 = ClassInfo::baseDataClass($var2);
$taint = ($var3 == 'Stage') ? $var1 :"{$var1}_{$var3}";

$var4 = "$taint";
//sink point: $taint;

$var5 = mysql_query($var4);
```

(b) CWE-89 Case

Figure 5: Two sets of sample Cases obtained through vulnerability reapir and RealVul. We mark the data flow and potential vulnerability statements.