LARGE LANGUAGE MODELS IN SECURITY CODE REVIEW AND TESTING

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Abstract

In this paper, we systematically present and discuss practical applications of Large Language Models (LLMs) in software security, concretely in code vulnerability detection, fuzz testing, and exploit generation. Measurements of various research outcomes are analyzed to answer questions about the performance of LLMs in those fields, including a comparison with tools that follow traditional approaches. In addition, the drawbacks and a future outlook, along with a delineation of technical challenges, are provided. Challenges include the cost- and time-intensive training of LLMs, the limited context-length understanding of program code, the high false positive rate due to hallucinations, and keeping the data up-to-date so that definitions of newly detected vulnerabilities are covered.

1 Introduction

Secure software development is a crucial topic, as vulnerabilities can compromise applications and services, which have become the foundational pillars of our daily lives. Moreover, many critical services are based on software-intensive infrastructure where confidentiality, integrity, and availability, i.e., CIA triad, are key requirements. Therefore, software security is a pervasive concern that can lead to incidents and breaches when implemented improperly.

Software development goes through different phases until the finished product is established. Additionally, each phase has distinct security aspects that must be taken into consideration. Various methodologies provide a structured approach to secure software development. For instance, the SecDevOps lifecycle provides an overview of security topics that should be checked during software development and operation [13]. Similarly, the Secure Software Development Lifecycle (SSDLC) also targets security but with a focus on software development [14]. Ultimately, all these methodologies and frameworks share several common traits: efficient and diligent vulnerability detection and testing are crucial.

Since the emergence of LLMs, they have garnered significant attention from developers for their potential to achieve secure software. The focus of interest for LLMs stems from its architecture, which was first introduced in 2017 by Vaswani et al. [49], in the current form. The architecture, comprising an encoder and decoder, employs a so-called attention mechanism, allowing the LLM to focus on relevant input sequences. For training, enormous datasets are used, encompassing a wide range of topics. The aim is to create foundation models, which can be used in various ways [3]. For example, LLMs are already used on different topics, ranging from medicine to education, and also in software engineering [25], whereas software security represents a new research field.

In this paper, we provide a systematized description of LLM's role in software security, namely for security code review and testing. We present a high-level introduction to LLMs, including a technical description, a definition of the terminologies used, and LLM training methods (Section 3). The focus relies on secure implementation and security testing of software. Firstly, we elaborate on automated static code vulnerability detection in Section 4. It serves as an ideal entry point for a first security check before merging the code into the codebase in software development. Another technique for finding vulnerabilities is fuzz testing (Section 5). Here, we focus on the creation and mutation of fuzzer input while also including the generation of the fuzz driver as a second subtopic. In Section 6, we also want to show how these detected vulnerabilities can be converted to exploits by using an LLM as an automated exploit generator. Lastly, we discuss our findings in relation to our research questions, outline the challenges of implementing LLM approaches in this domain, and provide an outlook on potential future developments (Section 7).

Research questions - We build our systemization of knowledge for our scope around the following research questions in this work:

1. What are practical use cases for LLMs in security code review and testing, and how do they perform against traditional tools?

2. What is the impact of LLM itself (i.e., core aspects such as recency, parameter count, and prompting techniques) on the performance of proposed solutions?

3. What are the current approaches for improving the performance of LLM-based solutions in our use cases?

4. What are the current challenges, and what are the prospects for LLMs in security code review and testing?

Topic	Author	Description	LLM					Techniques			
			BERT	Davinci	Llama	OpenAI	Other	Tuning	Prompt	Tool	Dataset
C	Cheshkov et al. [10] in 2023	Cheshkov et al. created a performance comparison using GPT models from OpenAI in code vulnerability detection by categorising the vulnerability with a binary and multi-label classification approach.		x		x			x		x
C, E	Fu et al. [20] in 2023	Here, the whole lifecycle was considered. This includes tasks like vulnerability detection and its classification, a risk assessment, and a proposal on how to mitigate the security risk.	x			x		x	x		x
C	Guo et al. [24] in 2024	Different LLMs with varying training backgrounds were chosen to conduct a comparison in a binary classification task. Six LLMs are especially trained for vulnerability detection, while the other six LLMs were only fine-tuned or taken as is without special training.	x		x	x	x	x	x		x
C	Purba et al. [41] in 2023	They compared different LLMs and traditional tools by using two different datasets to see whether the vulnerability is detected or not.		x		x	x	x	x		x
C	Tamberg and Bahsi [45] in 2025	Tamberg and Bahsi analyzed the use of LLMs in code vulnerability detection by testing different prompt strategies and comparing the results with the performance of traditional tools.				x	x		x		x
C	Yin et al. [54] in 2024	Yin et al. not only considered the vulnerability task but also researched how capable LLMs are in detection, risk assessment, location, and reporting of vulnerabilities.	x		x		x	x	x		x
C	Yu et al. [55] in 2024	Yu et al. applied five different prompts and evaluated which of them led to the best performance, also in comparison to traditional tools.			x	x	x		x		x
F	Black et al. [8] in 2024	They analyzed the effectiveness of LLM in seed generation in combination with the existing fuzzer Atheris, especially for the programming language Python.				x	x		x	x	
F	Tamminga [46] in 2023	Tamminga focused on an approach for using an LLM as a seed generator in combination with traditional fuzzers, such as AFL++ and libFuzzer. While focusing on the programming language Go, a priority was placed on interoperability between different programming languages.				x	x	x	x	x	x
F	Xia et al. [52] in 2024	Xia et al. demonstrate a practical implementation of a mutation-based fuzzer, known as Fuzz4All.				x	x		x	x	
F	Zhang et al. [59] in 2024	They created a tool, called LLAMAFUZZ, which can be used to enhance greybox fuzzing.			x			x	x	x	x
F	Zhang et al. [58] in 2024	Zhang et al. demonstrate how an LLM can be used in fuzz driver creation.			x	x	x		x		x
E	Fang et al. [18] in 2024	The focus is on exploit generation for one-day vulnerabilities using LLMs.			x	x	x		x		x
E	Zhang et al. [60] in 2023	The topic is about generating exploits using an LLM. It focuses on the use case of dependency vulnerability alerts and the reduction of false positives. The result is then compared with traditional tools.				x			x		x
E	Zhou et al. [61] in 2024	Zhou et al. present a tool called Magneto, which uses fuzzing techniques to exploit unpatched vulnerabilities from third-party dependencies.				x			x	x	x
O	Jiang et al. [29] in 2024	Here, the challenges as well as recommendations are considered. They focus on research done in LLM-based fuzzing.	-	-	-	-	-	-	-	-	-
O	Kaddour et al. [30] in 2023	Kaddour et al. give a general overview of the current challenges encountered when applying LLMs in practical fields.	-	-	-	-	-	-	-	-	-

Table 1: Overview of the related work (- : Not applicable).

2 Methodology

In this paper, we focus on technical works that utilise LLMs in software security. We defined a process to search for and select suitable research papers, outlining the criteria using the proposal by van Wee and Banister [48] as inspiration for our methodology. Our focus topics are "code vulnerability detection (C)", "fuzz testing (F)" and "exploit generation (E)". To ensure readability, we will use the abbreviations defined in the brackets.

In the first step, we defined search keywords to use within the databases. A complete list of the used keywords can be found in Table 2, which depicts the topic and the corresponding search terms. The search terms are primarily structured based on the topic, including the keyword "LLM".

Topic	Search String
C	ChatGPT for Code Vulnerability Detection
C	LLM for Code Vulnerability Detection
C	LLM for Software Vulnerability Detection
C	LLM for Security Code Review
F	LLM in Fuzz Testing
F	LLM in Fuzz Driver Generation
F	LLM for Seed Generation in Fuzzing
E	Exploit Generation with LLM in Software Development

Table 2: Search terms.

Secondly, we applied those keywords to academic publishing venues and meta-search engines to find relevant papers. Concretely, we used the following databases:

- ACM [1]
- arXiv [5]
- Elsevier [17]
- Google Scholar [22]
- IEEE [28]
- Springer [43]
- Wiley [51]

Lastly, we applied our selection process, presented in Figure 1. We began by conducting a short metadata review of each paper. We also looked at the reputation and citation score. However, since the systematized knowledge and relevant works in this domain all revolve around fast-moving research, these scores did not strictly determine the selection, but rather provided crucial guidance. This was particularly true when we could not find works with a similar scope. Afterwards, we checked important text passages like the abstract, discussion, and conclusion for a first assessment of the topic coverage. In this step, we ensured that the paper's content aligned with our research questions and that the LLM was a primary component. The next step was skimming over the paper. Since we were interested in practical examples, we excluded papers with only theoretical coverage. Additionally, we wanted to ensure that the papers contained valuable insights for us, particularly by covering benchmarks and comparisons with traditional tools. In a detailed examination, we focused on the LLM techniques employed and excluded duplicates or papers covering similar topics that provided no additional insights. Lastly, we performed snowballing by analysing the references used by the papers to identify potential new candidate papers.

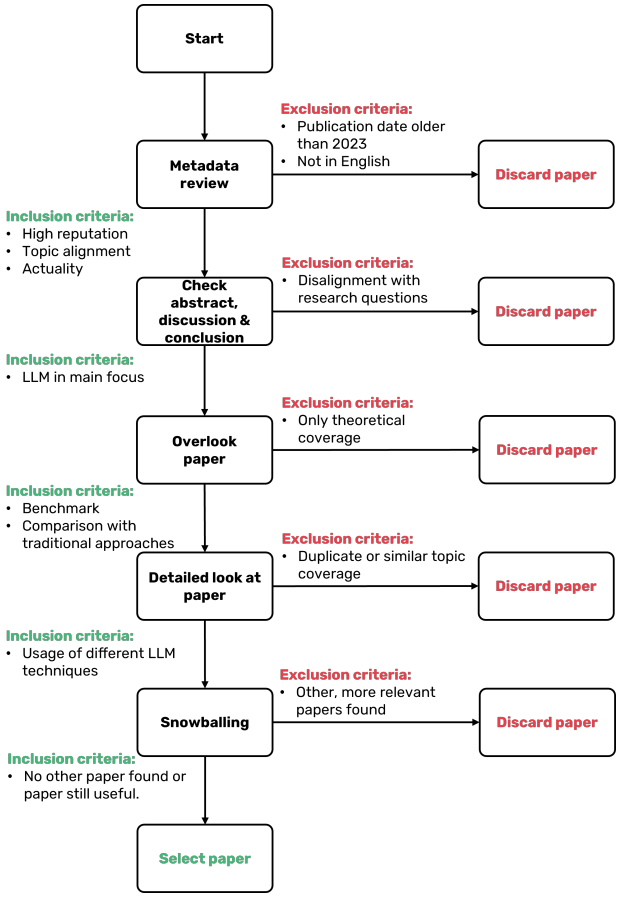

Figure 1: Paper selection process (adapted from [48]).

In addition, survey papers were examined to gain an overview of current works and the technical domain. The listed papers were also manually post-filtered to avoid duplication, misselection, and quality issues. At the end, 17 papers were selected. Please note that our work is not an exhaustive literature survey paper but a Systemisation of Knowledge (SoK) paper presenting a concise and structured analysis of a focused scope. Ultimately, the scope includes LLMs for code vulnerability detection and testing, including fuzzing and exploit generation. A practical challenge remains in comparing

the selected papers as a single group. The foundation of the relevant research outcomes differs fundamentally. Often, different LLMs, testing datasets, techniques, and approaches are used, making a direct comparison between those selected papers difficult. However, we are interested in their outcomes and key findings. Having a broader view of the performance results of different papers makes it possible to draw conclusions about the current state-of-the-art and remaining challenges. We thus cannot provide a direct comparison between the papers, but we can provide a high-level comparison by analysing the outcomes of the individual papers together.

In Table 1, an outline of those surveyed papers is given. We categorised them into the three aforementioned categories and the additional topic "challenges and future outlook (O)". The final category was facilitated to provide a discussion on potential future technical research and development directions. The table consists of metadata information like author, year, and a short description. Further, an overview is provided about the used LLMs in those works as well as the applied techniques, as listed below:

- Tuning: The paper includes fine-tuning mechanisms.
- Prompt: The paper applies prompt engineering techniques.
- Tool: The paper introduces a tool for a specific task with an advanced architecture, in which the LLM plays a significant role.
- Dataset: The paper creates or introduces a dataset that can be used for training or testing.

The research in this field is progressing rapidly. Each new version of an LLM can bring improvements in performance. This makes it particularly challenging to provide long-term value within this paper, since the current measurements are already outdated with the next iteration. However, we think that the currently used techniques and application areas will continue to exist in the same or a similar form. In other words, the identified research vectors will also be valuable in the future. Therefore, well-functioning concepts should continue to be used in the future to obtain better results from LLMs. Moreover, circumventing the technical limitations will remain valid for some time. In light of these points, we believe that this paper will provide long-term value for the research community as well as practitioners in the industry.

3 Large Language Models (LLMs)

The task of a language model is to predict and generate language. To do that, the likelihood of the next upcoming word needs to be calculated [2]. To illustrate, if we consider the sentence "I need an umbrella because it is ..." the next best-guessed word could be "raining". There are different approaches and concepts for constructing a language model [2]. Initially, statistical language models were employed, which are based on calculations performed on text-containing datasets. One implementation is the n-gram language model, which predicts the next word based on the previous n-1 words [2, 3]. Following the introduction and rise in popularity of neural networks, the underlying technology in language models underwent significant changes. With a neural network, one could improve its parameters to get optimised outputs by applying training methods using training datasets [2, 3].

A step forward was achieved with the transformer architecture, which was introduced in 2017 by Vaswani et al. [49]. This architecture, based on a deep neural network, enables the creation of LLMs [2]. The name affix "large" comes from the count of parameters or the size of the used training dataset [23]. For example, Llama 2 has 70 billion parameters and used 10 TB of text for training, according to Karpathy [33]. The architecture builds on a so-called attention mechanism, which uses weights to distinguish the vital parts from the input [2]. It consists of an encoder and decoder, but some approaches use only one of the two parts [3]. The encoder processes the input and tries to understand it by depicting it in a suitable format. The decoder, on the other hand, is responsible for generating the result by taking the encoder's output as input [3].

In Figure 2, the LLM architecture, as well as the training steps before it can be used by a user, are visualised. The initial training of an LLM is referred to as pre-training, and it is both cost- and time-intensive [33]. The reason lies in the training process itself, which requires the gathering of a large amount of information and the calculation of numerous parameters. For example, Llama 4 Maverick [37] has a total of 400 billion parameters, while DeepSeek-V3 [15] has a total of 671 billion parameters. For this reason, pre-trained, foundation LLMs are used as a base and, if needed, adjusted via fine-tuning [3].

The fine-tuning process begins with the gathering of labelled datasets. This training data typically contains examples similar to the data used for the classification task in production. In the next step, the labelled training data is used to fine-tune the model. As a result, an adjusted model is obtained. Fine-tuning is an iterative process. As soon as the productive model is rolled out, logs should be gathered to correct anomalies by applying the described process again [33].

Another adjustment technique is prompt engineering. It focuses on the input, which gets passed to the LLM. Various patterns can be used so that the LLM generates output within the boundaries given by the patterns. Sahoo et al. [42] created a survey, describing common prompt patterns. Creating prompts without further refinements is called zero-shot prompting. In few-shot prompting, examples are included, intending to give the LLM a clearer instruction. A different approach is the so-called chain-of-thought prompting. Here, the LLM is guided on how to calculate the result, such that it shows its calculation steps. Moreover, many other abbreviations exist using similar ideas [42].

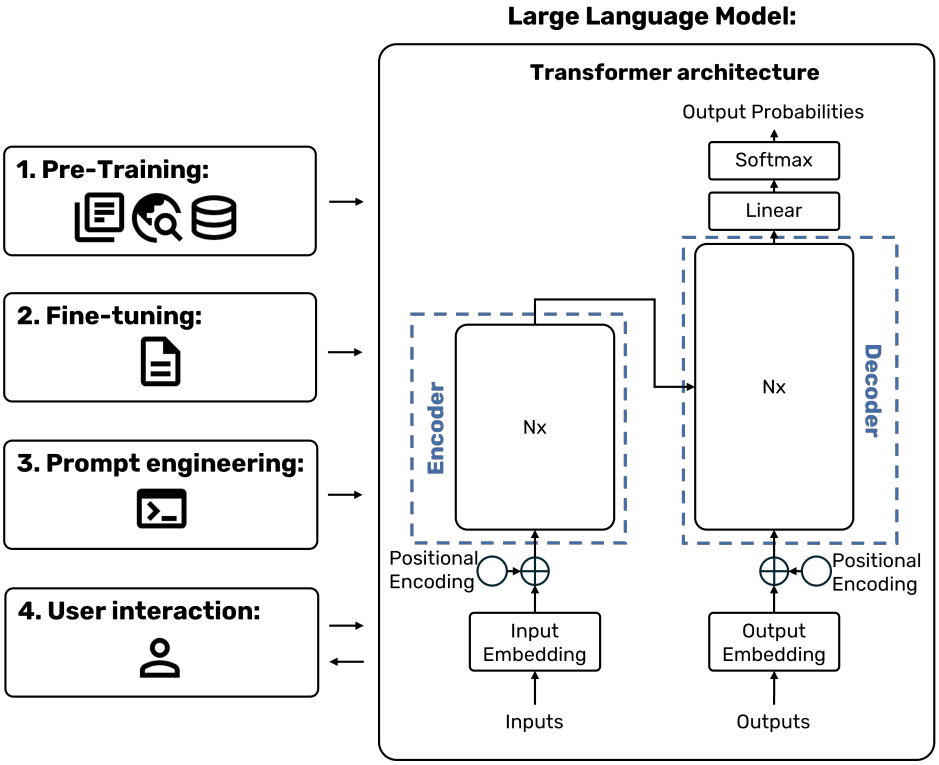

Figure 2: Architecture of LLMs and training methods (adapted from [3, 49]).

4 Automated static code vulnerability detection

Code review is a technique used in software development, where the code gets reviewed by a second person before it is merged into the productive codebase [6]. There are different reasons to conduct code reviews, some of which are shown in the study of Bacchelli and Bird [6]. In their survey, they show that the motivation for doing code reviews is to increase the overall code quality level of the codebase, find and eliminate bugs to reduce the error ratio, and for know-how transfer. In this section, we will focus on security code review, which is a subcategory of error finding by aiming to detect and find security flaws in software [16].

Although code reviews offer benefits, they are not always conducted due to various factors. Codegrip [12] and Ghanbari et al. [21] have addressed the question of why code reviews are neglected. Both came up with similar reasons. One reason was the increased workload and time costs for carrying out a code review. A company might tend to overlook code reviews in order to achieve certain goals and increase productivity. Another reason mentioned by both was motivation. The software development team may be disinterested in applying code reviews because of a lack of interest — not understanding the benefits, or having a false sense of risk [12, 21]. An additional reason given by Ghanbari et al. [21] was the technical complexity of the project environment, leading sometimes to negligence in applying code quality improvements. Bacchelli and Bird [6] supplement the list by adding the understanding of code changes to the challenges. In their interviews with software developers, they found that the major challenge lies in understanding why the code change was made and what influence the change has on the software's functionality.

Another aspect is the way code reviews are conducted. There are two types: manual and automatic code reviews [12, 16]. Although most companies do manual code reviews [12], this is considered liable to errors, which is shown by the study of Edmundson et al. [16]. They measured the effectiveness of code vulnerability detection in manual security code reviews by interviewing software developers. On average, a software developer could find about a third of the known vulnerabilities. While this speaks in favour of using automated tools, only 27% of the surveyed companies in [12] are regularly using an automated code review tool. The reason lies in the missing know-how against such tools [12].

Because of those hindrances, new approaches are investigated to automate this process by using general-purpose LLMs. The benefit stems from the transformer architecture, which is trained on general data and therefore makes the LLM suitable for different tasks, with one of them being vulnerability detection in software [41]. There are two different types of automated tools. The static approach (Static Applica-

User Prompt

Is there a software vulnerability? Answer only with yes or no, the corresponding code line and the vulnerability type.

```
#include <stdio.h>
int main(int argc, char **argv) {
  char buf[8];
  gets(buf);
  printf("%s\n", buf);
  return 0;
}
```

ChatGPT Answer

Yes, `gets(buf);` - Buffer Overflow

Figure 3: Interaction with ChatGPT giving the task to detect code vulnerabilities (adapted from [38, 39, 41]).

tion Security Testing, SAST in short) is applied to the source code, while the dynamic approach (Dynamic Application Security Testing, DAST in short) is applied to the compiled and running application [11]. In this section, we will focus on techniques for static code vulnerability detection.

In Figure 3, an example is shown by using ChatGPT-4 [38] and a code example from OWASP [39]. The code example contains a buffer overflow vulnerability. In such a case, the application's memory is overwritten by exceeding the assigned memory, thereby causing unpredictable behaviour in the application [39]. The faulty line is the call to the method `gets()`, which is considered unsafe in C since it does not check the size of the buffer.

The task of the LLM is to notice the vulnerable code snippet. Including the code with a corresponding question to the prompt (similar to the research from Purba et al. [41]) leads to ChatGPT [38] detecting the vulnerability, pointing to the vulnerable code line, and explaining why the code is viewed as unsafe.

4.1 Adapting LLMs for code vulnerability detection

In the research by Purba et al. [41], they compared different LLMs and applied vulnerable code to measure how effective LLMs are in noticing code vulnerabilities. Furthermore, they compared base models and fine-tuned models. The latter were trained with labeled data containing examples of both vulnerable and secure code. As for the testing dataset, they used code examples containing buffer overflow and SQL injection vulnerabilities [41].

Similar to Purba et al. [41], Guo et al. [24] tested the capability of LLMs in the binary classification task with a similar prompt. In contrast, they compared the performance of differently trained LLMs. They included general-purpose LLMs, self-fine-tuned LLMs, and open-source LLMs that were already trained for code vulnerability detection tasks [24].

Cheshkov et al. [10] also evaluated how well GPT models perform in vulnerability detection. Like the previous two approaches [24, 41], they performed a binary classification but also added a performance measurement for a multi-label classifier. The multi-label classification was done by providing five different CWE vulnerability types and designing a prompt asking the GPT model if one of those five vulnerabilities is included in the provided code snippet [10].

Another technique that can influence the results of an LLM is prompt engineering. Thus, Yu et al. [55] designed five prompts and tested their effectiveness. They included an instruction and modified the prompt by adding or removing additional information, like project information or CWE descriptions, and using techniques like chain of thought. Tamberg and Bahsi [45] also followed the approach of testing different prompt engineering approaches by applying 23 different prompts inspired by related work.

Yin et al. [54] not only discussed whether LLMs can detect vulnerabilities, but they also investigated whether LLMs are capable of finding the specific affected code location, disclosing why it is seen as a vulnerability, and estimating the risk coming from the discovered vulnerabilities. They tested the performance of different base and fine-tuned LLMs by using public datasets. As for prompt engineering, a few-shot approach was chosen. The prompt contains a task description similar to the ones already seen, the code under test, and an indicator defining one of the four mentioned tasks [54].

Fu et al. [20] further extended this approach and included the whole lifecycle in their research. They measured the capability of GPT models to detect vulnerabilities, but also to classify them. Moreover, the GPT models were tasked with evaluating the severity of the detected vulnerability and proposing a mitigation [20].

4.2 Results

In the results of Purba et al. [41], Davinci, with fine-tuning, achieved the best score across all models considered. Nevertheless, it had an F1 score of 73.2% with a recall of 94% and a precision score of 60%, indicating that there is a high false positive rate (FPR). Similarly, all of the compared LLM models suffered from a high FPR. In contrast, the false negative rate (FNR) of the Davinci model was low at 6%. In the work from Cheshkov et al. [10], the binary classifier also had a high FPR, while the multi-label classifier led to a lower F1 score and a lower precision and recall score. Thus, that work did not perform well for both classifiers.

Guo et al. [24] made two key findings: Firstly, LLMs perform well on known vulnerabilities seen through the training dataset, but are limited in the generalisation of their learned knowledge. Secondly, fine-tuning enables smaller LLMs to be better than larger LLMs in certain tasks. However, a problem encountered during training, which could also affect the results of other research, was the inaccuracy of the dataset [24].

As for the prompt, Yu et al. [55] observed that the prompt with an instruction and containing specific information about

the CWEs performed the best. Tamberg and Bahsi [45], who also made a prompt-based approach, concluded that different models react differently to the prompt. For GPT-4 Turbo, the best result could be reached with a dataflow analysis prompt. This prompt includes a task description, which demands an analysis of the data flow within the provided source code and a template on how to answer. After receiving the answer, a second and a third prompt were added, in which the LLM is asked to review and improve its answer. For GPT-4 and Claude 3 Opus, the highest result was reached with a chain of thought prompt. Here, the process of how to approach the problem step by step was described, so that the LLM can follow this manual [45].

Yin et al. [54] concluded that there is potential for LLMs in the covered tasks, but they still need development. In the analysis from Fu et al. [20], they deduced that base models of ChatGPT are not suitable for use in all four observed tasks because of their poor performance.

4.3 Comparison with traditional tools

Contrary to LLM, Purba et al. [41] and Tamberg and Bahsi [45] provided an overview of the performance of traditional tools that execute static code analysis. The traditional tools work by using syntactic and semantic checks. For example, a rule set for a syntactic check could contain a list of different vulnerable functions, such as the mentioned `gets()` function in Figure 3 [35]. To detect intricate vulnerabilities, semantic checks are necessary. Here, the codebase is transformed into an enhanced control flow representation, allowing for a more sophisticated vulnerability detection approach [35].

In the research of Purba et al. [41], the tool Checkmarx[1] performed the best among the traditional tools with an F1 score of 47.3%. Compared to LLMs, this tool keeps a lower FPR at 43.1% but has a higher false negative rate (FNR) at 41.1% [41].

Tamberg and Bahsi [45] came to a similar conclusion regarding the FPR. However, their model achieved higher precision at the expense of lower recall compared to the Davinci model from Purba et al. [41]. One explanation for this outcome could be the overall performance gain with newer models, as [45] was published in 2025 using GPT-4, whereas [41] was published in 2023 using GPT-3.5-Turbo. However, the reason could also rely on the usage of different prompts, fine-tuning strategies, or the dataset used for the benchmarking.

A performance comparison from Purba et al. [41], and Tamberg and Bahsi [45] can be seen in Figure 4. Overall, one can say that traditional tools focus on keeping the false positives low by compromising on false negatives. However, this approach allows developers to focus on relevant findings without losing time on false positives. In contrast, LLMs are finding more true positives but with more false positives, handing over the task to developers to filter them out.

[1]Checkmarx: https://checkmarx.com/

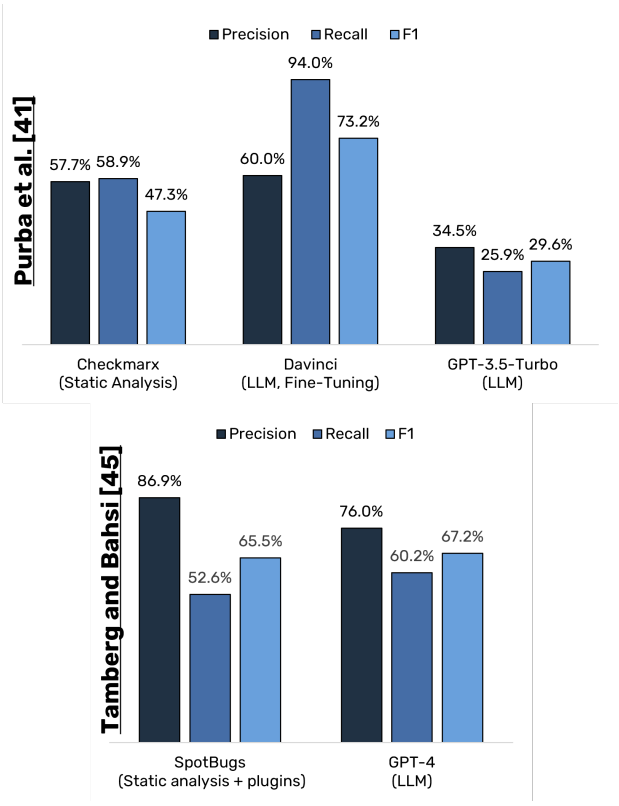

Figure 4: Performance comparison of different code vulnerability detection tools (adapted from [41, 45]).

5 Fuzz testing

Fuzz testing describes the method of using randomised input to test how a function reacts to it. The intention is to observe unusual behaviour and thereby to detect code flaws and potential vulnerabilities [56]. While it is considered effective in discovering software vulnerabilities, various hindrances prevent the use of this technique in the industry.

Firstly, the complexity of the environment setup needs to be taken into account. Fuzzers have different requirements before they can be applied. Since an existing environment uses various technologies, including operating systems, programming languages, and external libraries, it is difficult to adapt it to a fuzzer.

Secondly, fuzz driver implementation is challenging. A fuzz driver describes the link between the test function and the API. Thus, software developers need to know how the software works in technical and functional detail so that they can write a precise abstraction layer of the function for use in fuzzing [57].

For these reasons, research is done to automate the process. LLMs are also considered, as their general-purpose implementation allows them to adapt better to existing setups. This section focuses on using LLMs in fuzz testing, discussing the potential of LLMs in this field.

5.1 Input generation with LLM fuzzers

A fuzzer can be viewed as a generator that creates random inputs [56]. Since the underlying implementation of the generator can vary a lot, different types of fuzzers exist in practice. In the work of Beaman et al. [7], a definition for the various types was created, depending on how advanced the fuzzer is. A fuzzer is mainly categorised by the knowledge it has about the function and the system under test, and also by how it generates the input and how it reaches the testing coverage. In Table 3, we give an overview of the different classification types and a short description based on the definitions from Beaman et al. [7]. Additionally, the table categorizes the fuzzing-related research covered in this work.

5.1.1 Seed generation with LLM

Seed generation is fundamental for fuzzers, since it represents the basis of the inputs. It is challenging because it requires knowledge of the underlying functions, the technologies used, and the specifications of the software. In addition, the use of existing solutions may be impractical if the used tech stack is not compatible [8,34]. Because of the discussed obstacles, automated tools are preferred. Such automated tools are covered in the work of Tamminga [46] and Black et al. [8].

Tamminga [46] investigated if an LLM can be modified to use it as a seed generator for the existing fuzzer libFuzzer[2] and on the programming language Go, but with the aim to be independent of the used tech stack. As a basis, pre-trained LLMs were used and compared against each other. Furthermore, the LLMs were optimised for seed generation by either using prompting or by fine-tuning using a self-created dataset [46].

Black et al. [8] focused their seed generator for the Atheris[3] fuzzer, which is a fuzzer for the programming language Python. As for the prompt, a task description, the function under test, and a description of the expected output were included. To test the effectiveness of seed generation with LLM, they created a testing pipeline that allows the generated seeds to be passed to the function under test [8].

To measure the performance, Tamminga [46] created an evaluation method based on the core idea of the benchmarking process Magma, which was developed by Hazimeh et al. [26]. The benchmark includes measurements about the count of detected bugs and the time within which they were discovered [46]. Ultimately, StarCoderPlus with prompt engineering could detect 39% of the crashes within 30 seconds, while 64% were triggered within 10 minutes. In comparison, libFuzzer without any seed generation only reached 23% in 30 seconds, but also 64% in 10 minutes. A performance summary, based on the measurement from Tamminga [46] is in Figure 5 visualised.

Black et al. [8] used the reached coverage as a performance

[2]https://llvm.org/docs/LibFuzzer.html
[3]https://github.com/google/atheris

Type	Definition	Research
Input knowledge		
Dumb	It follows strictly its seed generation process.	-
Smart	Alters the seed generation process to better suit the function under test.	[8, 46, 52, 59]
System knowledge		
Black-box	It has no information about the underlying system.	-
White-box	It has all the information about the underlying system.	-
Grey-box	It is a mix between black-box and white-box, where it has partial information about the underlying system.	[8, 46, 52, 59]
Generation method		
Random	It creates seeds randomly.	-
Generation-based	It generates seeds based on certain parameters and routines.	[8, 46, 52]
Mutation-based	It mutates already generated seeds by adding, removing, or changing parts from the seed.	[52, 59]
Testing coverage		
Directed	It tests a specific part of the code or function.	[8, 46, 52, 59]
Coverage-based	Code coverage describes the parts of the code that were executed by the calling function. The aim is to achieve the highest possible code coverage.	[52]

Table 3: Overview of the different classification types of a fuzzer (based on [7]).

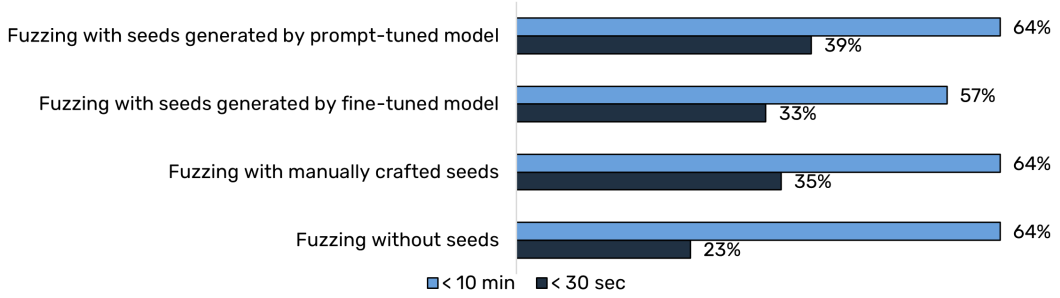

Figure 5: Comparison of libFuzzer with different seed generation approaches (adapted from [46]).

measurement. As for the tests, they had three different approaches. The first approach uses only the fuzzer. In the second approach, a combination of fuzzer and LLM is used, and in the last approach, only the LLM is used. While there was no clear winner, the combination of fuzzer and LLM performed the best in most of the test cases, while for the other test cases, fuzzing alone or LLM alone were better [8].

5.1.2 Mutation-based fuzzer with LLM

Fuzz4All, developed by Xia et al. [52], goes one step further and takes mutation generation into account. It implements a fuzzer, which is independent of the used tech stack and can be used for a wide range of programming languages. In their work, they present how Fuzz4All is designed and what steps it runs through. To get fuzzing inputs, the user has to provide information for Fuzz4All. This can include documentation, manuals, or the application code. The input is then applied to the autoprompting step. Since this information is written in natural language, while the expected output should be code, Fuzz4All uses two LLMs; one is used for the distillation phase, while the other is used for the generation phase.

In the distillation phase, the LLM attempts to understand and bundle the provided user information and to represent it as candidate prompts containing only the relevant information. Those candidate prompts are then passed to the generation phase, in which another LLM tries to generate fuzzing inputs. Afterwards, the candidates are evaluated against the function under test by executing a fuzzing test. The evaluation calculates a score based on criteria like code coverage, triggered crashes, or, like in the example of Xia et al. [52], the validity of the input. The candidate prompt with the highest score is then used as the initial prompt.

The next step in Fuzz4All is the fuzzing loop. It is an iterative process for generating fuzzing inputs. Some substeps are thereby similar to those of the autoprompting step. Firstly, the initial input prompt is applied to the generation LLM, which generates fuzzing inputs. Secondly, the fuzzing input is applied to the function under test to verify the validity of the fuzzing input and, ultimately, to trigger bugs. With this process, code snippets are gained, which can be applied as fuzzing inputs. Since the aim is to gain as many different inputs as possible, a mutation step is applied. It mutates the code snippet based on a randomly chosen strategy, enabling the LLM to generate different fuzzing inputs. There are three mutation strategies. Either the code snippets are mutated, semantically changed, or completely newly generated. Lastly, the output is used again as input for the LLM generation. This process is applied iteratively until a stop criterion is met [52].

This structure has different advantages. Firstly, since two LLMs are in use, one can choose them according to their capabilities. For the distillation phase, an LLM with a good understanding of natural language should be chosen. The second LLM used in the generation phase should be trained for code generation. Secondly, time efficiency can be achieved since smaller LLMs can be used, as they only need to focus on specific tasks [52].

Compared to traditional fuzzers, this approach generates fewer valid inputs, but it achieves a higher coverage in less time. Figure 6 shows the comparison of Fuzz4All with traditional tools based on the measurement from Xia et al. [52].

5.1.3 Greybox fuzzing with LLM

Zhang et al. [59] implemented a tool called LLAMAFUZZ, which is used for improving greybox fuzzing. Their approach consists of connecting the ALF++[4] fuzzer with Llama 2. While the LLM is used for input mutation, the fuzzer has the task to execute the generated input in the function under test, to monitor the execution, and to pass the result back to the LLM [59].

LLAMAFUZZ could outperform traditional tools by reaching a higher code coverage and achieving a higher bug count. Overall, it increased the code coverage by 27.2% in comparison to AFL++ without LLM enhancement and detected 41 bugs more on average [59].

[4] https://aflplus.plus/

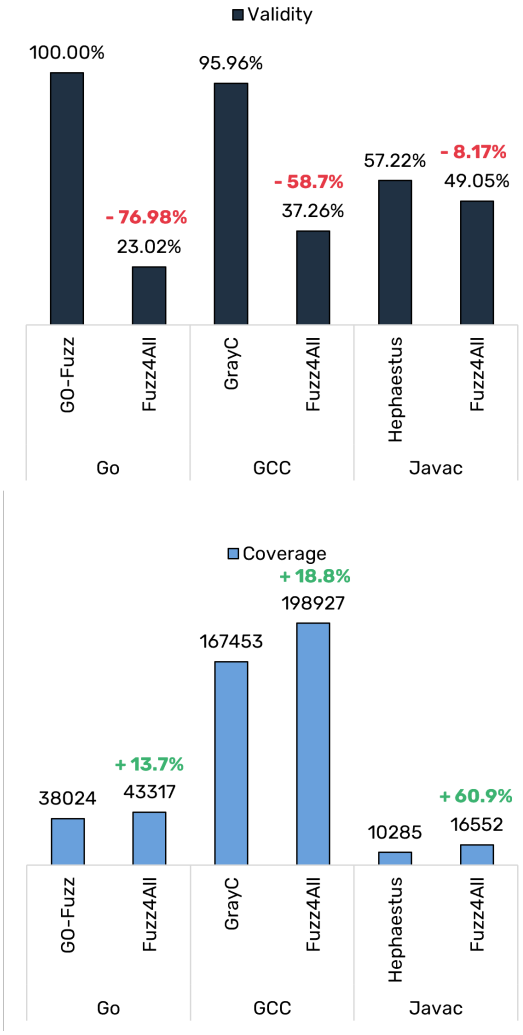

Figure 6: Validity and coverage comparison between Fuzz4All and traditional tools (adapted from [52]).

5.2 Fuzz driver generation

A fuzz driver describes the link between the system under test and the fuzzer by providing an API. This is a laborious task since they are typically written manually [57]. Additionally, the API needs to be as precise as possible since mistakes in the implementation could increase the falsification of the result for the system under test [58].

Zhang et al. [58] considered different approaches for prompt engineering an LLM to gain a fuzz driver generator. The best-performing strategy they found is iterative prompt processing. The strategy consists of a generation and several fix prompts. As seen in Figure 7, the prompt consists of a task description for the LLM, a code documentation, and a code snippet of the API. ChatGPT gives, in this case, a proposal of how implementing the function "FuzzerTest" could look. The output can also be seen in Figure 7. Afterwards, one or more fix prompts are applied on cases where the produced LLM output has compilation errors [58].

User Prompt

```
// The following is a fuzz driver written in C language,
// complete the implementation. Output the continued code
// in reply only.
#include "example/array.h"

/*
* @brief: Gets the element at the given index.
* @param: index of the element
*/
extern int getArrayNumber(size_t index)

// the following function fuzzes getArrayNumber
int FuzzerTest(const uint8_t *Data, size_t Size)
```

ChatGPT Answer

```
{
  if (Size < sizeof(size_t)) {
    return 0; // Not enough data to extract an index
  }

  // Extract index from the input data
  size_t index;
  memcpy(&index, Data, sizeof(size_t));

  // Call the function being fuzzed
  int result = getArrayNumber(index);


  // Perform any sanity checks or validations on the result
  // For now, we'll simply return success
  return 0;
}
```

Figure 7: Generation prompt and output from ChatGPT (adapted from [38, 58]).

During the investigation of fuzz driver generation with LLMs, Zhang et al. [58] discovered that the performance depends on the complexity of the API. An LLM needs to be able to forecast how an API works based on the given questions and user inputs. Therefore, it can be concluded that as the complexity of the system under test increases, the

performance of the LLM decreases. The best performance was reached by GPT-4, which could answer 78 out of 86 questions in the right configuration [58].

LLM-aided fuzzing is already used in practice. In 2023, Google [36] added LLM to their OSS-Fuzz project. It is used to automate vulnerability detection, mainly in open-source software. While doing so, they found that, in some cases, the code coverage was improved. In one case, they increased the code coverage by over 30%. To reach the same level for all OSS-Fuzz projects, they stated that "several years" of manual adaptation would have been necessary [36].

6 Exploit generation for software testing with LLM

As discussed in Section 4, LLM suffers from a high FPR. But traditional approaches also have false positives [55]. This causes software developers to question the results of automated vulnerability detectors. Therefore, showing if and how a vulnerability is exploitable is essential [60]. One example is a dependency vulnerability detector. When it reports a vulnerability in one of the used libraries, it does not necessarily mean it is exploitable in the application. A way of showing the exploitability of a vulnerability is to write an exploit [60].

6.1 Research approaches

In the research of Zhang et al. [60], ChatGPT-4 was used to generate security tests, which could then be used to test the exploitability of the vulnerable dependency. The following parameters were included in the prompt [60]: *Task description, function name, vulnerability ID, vulnerable API list, test function name incl. an exemplar test implementation, and client code implementation*. When the LLM output contained smaller errors, a manual process was applied to correct the output.

Fuzzing, which we discussed in Section 5, was used by Zhou et al. [61] in their tool called Magneto. It aims to exploit vulnerabilities in complex environments. In their paper, they explain how the mechanism of Magneto works. In a first step, information about the vulnerability itself is collected, including the affected version and the functions, as well as an exploit and its oracle. This information is then compared with the dependency tree of the software project, and only the dependencies matching the vulnerability description are kept. Afterwards, Magneto tries to understand the underlying architecture of the software by depicting the call chains of the software under test. Based on the gathered information, Magneto tries to exploit the vulnerability. For this, Magneto needs to find an input so that it can be passed to the function on top of the call chain while also remaining a capable input to trigger the vulnerability on the dependency under test. Its approach is done incrementally, by trying out different seeds, which are created by an LLM. It starts with the function call to the dependency and works its way up until it reaches an exposed function. With this approach, the function may be able to find a vulnerability [61].

Fang et al. [18] analyzed the efficiency of LLM in exploit generation for one-day vulnerabilities. To achieve this, they used different LLMs and leveraged them for exploit generation. The LLMs were provided with different resources, such as a web browser, a terminal, and the ability to use a code interpreter and to create or modify files [18].

As already discussed in Section 4, Fu et al. [20] had a look at a variety of tasks in the software vulnerability spectrum. Here, we want to take a glance at the automated severity estimation and mitigation of vulnerabilities with LLM. For the severity estimation prompt, Fu et al. [20] proposed to include a description of what the LLM has to do and to include the vulnerable function. For the mitigation prompt, they included several generic examples of vulnerable functions and their repair methods with a task description, which is similar to a few-shot prompting approach [20].

6.2 Performance comparison

Zhang et al. [60] tested the GPT model on 55 apps containing vulnerabilities. As a result, in 24 cases, the vulnerability could be successfully exploited. In addition, a comparison was made with the traditional tools SIEGE [27] and TRANSFER [32]. While TRANSFER [32] achieved writing four exploits, SIEGE [27] could not generate one. This leads ChatGPT to surpass them [60]. Magneto, created by Zhou et al. [61], was at least 75.6% more successful in creating an exploit compared to traditional tools like SIEGE [27], TRANSFER [32], and VESTA [9].

Fang et al. [18] tested their prompt-engineered GPT-4 model against the traditional tools ZAP [5] and Metasploit [6]. In the end, they found out that the traditional tools, as well as the other considered models, were unable to generate exploits. Only their GPT-4 model could create exploits, but with a success rate of 87%. To perform that well, the inclusion of the CVE description in the prompt was mandatory [18].

For the severity estimation and mitigation task, Fu et al. [20] reached a sobering conclusion, as the model was unable to sufficiently estimate severity or propose mitigations.

7 LLM challenges and future outlook

In this section, we delineate our key takeaways, presented through the lens of the information gathered from the papers listed in Table 1, and discuss the challenges and potential future approaches. The identification was made by mapping the mentioned challenges from the discussed papers while also considering the general difficulties of LLMs.

[5] https://www.zaproxy.org/
[6] https://www.metasploit.com/

7.1 High False-Positive Rate (FPR)

A problem encountered in the discussed topics was the high FPR and the low accuracy, which was discovered by various researchers [10, 20, 29, 41, 45].

The recommendation from Cheshkov et al. [10] is to invest further research in prompt engineering. Having a more enhanced prompt, like the proposed chain-of-thought technique, could lead to better performance in the LLM for code vulnerability detection [10]. To correct the errors produced by the LLM, Jiang et al. [29] suggest using the LLM again for output correction. This enables the LLM to improve its output by gaining insights into bugs introduced in its previous output.

An explanation can also be found in hallucination. Hallucination describes the effect of an LLM that writes factually incorrect outputs [31]. According to Kamath et al. [31], a reason for this behaviour could be a lack of knowledge because of missing, biased, or untrue training data in the pre-training process. To mitigate some of the named reasons, a common technique is retrieval augmented generation (RAG), which aims to include external knowledge sources [4]. We describe this technique in more detail in Section 7.2.

Decoding strategies can also be a culprit for hallucination. They are often used to introduce randomness in favour of producing more natural-sounding language. Therefore, new decoding strategies are designed to diminish hallucinations [30]. Two examples are uncertainty-aware beam search [53] and confident decoding [47].

7.2 Outdated data

Another challenge encountered in training is keeping the information up to date. Some research from the field of code vulnerability detection [10, 20, 54, 55] and exploit generation [18, 61], handled with CWE and CVE definitions. While they used mostly already known CWEs and CVEs covering general vulnerability topics, it is essential that the information basis of an LLM is up-to-date to also understand new vulnerability definitions.

There are different new approaches used in updating the information of a model. The simplest one is to enhance the prompt by including missing information directly into the prompt. For example, this is shown by Fang et al. [18], where they had to include the CVE description to gain a well-performing model.

A new approach to facing this challenge is RAG. It enables an LLM to expand its knowledge base with additional resources, such as websites, databases, or other forms of data storage. Those reference points are then considered when a corresponding prompt is placed, asking for specific information [4].

Model editing can also be used for this challenge. It attempts to identify the incorrect information base of an LLM and modify it accordingly [30].

7.3 LLM training

Pre-training an LLM is cost- and time-intensive [30]. This limits the capability of researchers to create LLMs specifically designed for the purposes we discussed in this paper.

To reduce computational power requirements, efforts are made to understand so-called scaling laws. Specifically, in the context of LLM, the interplay between model size, data size, and computational power is examined. An alteration in one of those three resources could lead to a corresponding change in a different resource [50].

A common technique used today to bypass pre-training is to take a pre-trained model and fine-tune it. As found out by Guo et al. [24], this allows for better performance in some tasks compared to larger LLMs. However, it comes with its challenges, like finding high-quality datasets. This challenge was mentioned by Guo et al. [24], in which they made the finding that there was some incorrect labelling in the datasets, leading to wrong training of the LLM.

Another technique is to apply different prompt strategies as discussed in various works throughout this paper. The benefit stems from the relatively easy application, as no modification to the model itself is required. However, while guidelines and strategies exist, such as those discussed by Sahoo et al. [42], it is challenging to determine which prompt yields better results [30], making it a trial-and-error process.

Also, the requirements for the setup have to be considered, since they are similar to those for pre-training. To fine-tune a model, it must be downloaded, installed, and executed [30]. Parameter-efficient fine-tuning (PEFT) is a recent technique to train the LLM for a specific task. The fundamental concept is to add a final layer with trainable parameters. During training, only the parameters of the additional layer are modified while the other layers remain unchanged [44].

7.4 Limited context length understanding

The applications of the discussed areas in this paper require a deeper contextual understanding to perform well. As a data basis, software code is provided, which includes different information like the architecture, program logic, and documentation. An LLM has the requirement to understand the system under test and to perform the described tasks on it. However, LLMs have a limitation in understanding contexts, leading to the omission of essential parts [30]. A further effect can be seen in fuzzing, since the limited context length understanding leads to an increase in the creation of invalid seeds [29].

There are various approaches to tackling this type of challenge, which may be applied in the future. According to Kaddour et al. [30], current research focuses on enhancing the capability of attention mechanisms to comprehend a broader

context. Other research is focusing on length generalization to maintain the advantage of training LLMs on short inputs, while also being able to understand longer inputs. Kaddour et al. [30] also discussed using alternatives to transformers. Architectures like state space models (SSMs) [19] or receptance-weighted key value (RWKV) [40] are designed for understanding longer contexts.

8 Discussion

In this section, we summarize the key takeaways based on the analysis of the related work and make the connection to the research questions. We also provide additional insight by offering tips and recommendations.

8.1 RQ1: What are practical use cases for LLMs in security code review and testing, and how do they perform against traditional tools?

LLMs have their rightful place in the context of security code review and testing. While they reach practical relevance in some topics, others are still in the research stage. In the following subsection, we provide an in-depth analysis of the prospects for each topic.

8.1.1 Code vulnerability detection

LLMs in code vulnerability detection can overcome various challenges associated with the use of traditional tools, as their setup, application, and integration into the code base are simpler than those of conventional tools. However, the LLMs in the research suffered from a high FPR, limiting the capability of LLMs in this use case. In comparison, traditional tools focus more on true positives and thus reduce the exertions from developers. Based on these findings, our recommendation is to invest more effort in research and, if the setup allows, to utilize traditional tools for production in the meantime.

8.1.2 Fuzz testing

In fuzzing, LLMs have advantages. On the one hand, it is less time-consuming and can find coverage-increasing seeds faster than its traditional counterparts. On the other hand, it can be used independently of the technology environment, while traditional tools have mostly binding requirements.

According to the surveyed literature, LLMs can outperform traditional tools in input generation. This is also true for fuzz driver generation, which is already in use in productive cases. This makes LLMs valuable in the context of fuzz testing, especially for testing a wide range of projects. Our recommendation is therefore to convert research findings into practical applications and develop productive, marketable tools that enable the easy use of LLMs in fuzz testing. However, some challenges, especially in the limited understanding of complex implementations, remain.

8.1.3 Exploit generation

The included papers show that exploit generation has potential, especially since they outperform conventional tools. However, prerequisites must be met, such as providing specific prompt information or making manual adjustments, to function properly. Additionally, only certain LLMs achieve acceptable results, making it dependent on the chosen LLM.

This leads to our conclusion that, at the moment, LLMs can only be used to a limited extent for exploit generation. However, since traditional tools also do not perform well, manual effort is still needed in practice. Nevertheless, further research investigations should be made.

8.2 RQ2: What is the impact of LLM itself on the performance of proposed solutions?

The most important component in the considered tools is the LLM itself. There exist a lot of different LLMs with varying parameter count, training basis, etc. In the related work, various models, including both open-source and closed-source, were used. While the performance between those works is not directly comparable, some general conclusions can be drawn:

1. Prompt engineering and fine-tuning can improve the performance in most cases compared to their base counterparts.
2. Newer LLMs are usually better than their previous versions.
3. While improvements can be achieved with techniques already mentioned, an indicator for better performance can also be the parameter count, while LLMs with more parameters should perform better.

This is also reflected in related work, where using newer models leads to better results or even makes an approach possible. With the introduction of new models (i.e., GPT-5), the tests should be repeated so that the performance improvement can be measured. The parameter count of an LLM should also not be neglected. However, some works show that by applying prompt engineering or fine-tuning, the performance can be improved. Thus, this should be taken into consideration, especially if computational power is limited.

Choosing an LLM is a difficult undertaking and not always straightforward. Indicators of good LLMs include their introduction dates, with the newer ones being preferable, as well as their parameter count and general benchmarking results. Additionally, one can check whether a security-trained version exists. Nevertheless, comparing the different LLMs in

a benchmarking process is crucial for identifying the best-performing one.

Also, an interesting concept is to use a combination of LLMs. This allows for focusing LLMs on one specific task, making their tuning simpler.

8.3 RQ3: What are the current approaches for improving the performance of LLM-based solutions in our use cases?

Different techniques can be used to tweak LLMs to be more tailored to specific areas of application. Since we included a range of papers, different approaches were used for the same aim.

8.3.1 Prompt engineering

Prompt engineering is a common technique that involves designing and structuring a prompt. The aim is to instruct and teach the LLM on how to complete a task in a way that is understandable from the perspective of an LLM.

In the considered works, various prompts were tested, each containing different levels of information. One common finding was that prompts including more information were more successful. However, the information must be articulated and designed in a way that known challenges, such as limited context length understanding, are not triggered.

Since prompt engineering is not an exact science and varies from use case to use case, we propose trying different combinations of information sources and benchmarking them accordingly. Additionally, examining recent findings on prompt engineering techniques is worthwhile. However, there is no predetermined solution again.

8.3.2 Fine-tuning

Fine-tuning is more efficient than the training of an LLM and allows for supplementing the LLM with additional training datasets. Though in practice, finding qualitative and good training datasets is difficult. Having incomplete or false datasets could even worsen the performance of an LLM. Thus, the key takeaway is to apply fine-tuning; however, creating clean datasets should also be a focus point.

8.3.3 Tool creation

In the various topics considered, but especially for fuzz testing, researchers have created tools in which an LLM is only one part of the system. The advantage of combining LLMs and traditional approaches is the potential to achieve deterministic behavior for precise tasks. For example, for testing of seeds, a unit test is created that directly applies the generated seed to the function, reducing the false positive count. Whenever possible, deterministic tasks should be outsourced to dedicated processes, allowing for reduced hallucination for those tasks.

8.4 RQ4: What are the current challenges, and what are the prospects for LLMs in security code review and testing?

In general, the creation and training of LLMs is a common challenge. Due to the high cost and time consumption involved in creating an LLM, we recommend utilizing existing general-purpose LLMs and leveraging them through techniques such as prompt engineering and fine-tuning. Since fine-tuning itself is also resource-intensive, new methods like PEFT should be explored, especially when resources are missing for full tuning. Additionally, finding the right datasets for training can be challenging. The dataset requires cleaning, and any incorrect data must be removed.

Furthermore, pitfalls can be found in general LLM challenges like high FPR, outdated data, and limited context length understanding. While all topics suffer from those challenges, they are not affected equally.

8.4.1 Code vulnerability detection

For the code vulnerability detection task, the high FPR is the main challenge. A high FPR in this topic renders an LLM unusable, as software developers would need to check for more possible threats. Thus, the aim of future research should be to reduce the FPR, even if this would mean an increase in FNR. This would allow a developer to focus on true positives.

For this, aforementioned techniques like prompt engineering and fine-tuning should be used. Moreover, creating clean datasets should be a focus point, as they are currently missing. Moreover, a combination with the topic of exploit generation is conceivable, since this would allow for implementing a check.

8.4.2 Fuzz testing

In Fuzzing, FPRs can be mitigated with enhanced controls, such as applying software tests. However, in this case, the limited context length makes it challenging for the LLM to comprehend complex and extensive software.

Therefore, experimenting with the optimal prompt configuration is crucial. Also, providing the right amount of information is necessary.

8.4.3 Exploit generation

Exploit generation relies on data actuality, as it needs to know about new vulnerabilities. However, since training is cost-intensive, the knowledge base of LLMs suffers from outdated data. To overcome this challenge, we recommend using RAG and connecting the LLM to corresponding vulnerability databases.

9 Conclusion

Practical implementation areas for an LLM in software security can be found in code vulnerability detection, fuzz testing, and exploit generation. The LLMs can be applied to those tasks by using prompt engineering, fine-tuning, and creating dedicated tools.

However, the performance varies between those different disciplines. While LLMs achieve good results in fuzz testing, they need further research in code vulnerability detection and exploit generation. This is mainly attributable to challenges like hallucination, high training costs, data actuality, and the limited context length understanding. Those challenges lead to a high FPR in code vulnerability detection, poor performance in complex fuzz testing cases, and insufficient knowledge for exploit generation.

To overcome these challenges, we propose in future research to explore prompt engineering and fine-tuning further. What is more, modern technologies like RAG can help in improving data actuality, while PEFT can help reduce training costs. There are also new approaches that follow different directions. This includes agentic AIs as well as the expansion of their capabilities by connecting them to existing tools over the Model Context Protocol (MCP).

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