

A Large-scale Empirical Study on Fine-tuning Large Language Models for Unit Testing

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Unit testing plays a pivotal role in software development, improving software quality and reliability. However, generating effective test cases manually is time-consuming, prompting interest in unit testing research. Recently, Large Language Models (LLMs) have shown potential in various unit testing tasks, including test generation, assertion generation, and test evolution, but existing studies are limited in scope and lack a systematic evaluation of the effectiveness of LLMs.

To bridge this gap, we present a large-scale empirical study on fine-tuning LLMs for unit testing. Our study involves three unit testing tasks, five benchmarks, eight evaluation metrics, and 37 popular LLMs across various architectures and sizes, consuming over 3,000 NVIDIA A100 GPU hours. We focus on three key research questions: (1) the performance of LLMs compared to state-of-the-art methods, (2) the impact of different factors on LLM performance, and (3) the effectiveness of fine-tuning versus prompt engineering. Our findings reveal that LLMs outperform existing state-of-the-art approaches on all three unit testing tasks across nearly all metrics, highlighting the potential of fine-tuning LLMs in unit testing tasks. Furthermore, large-scale, decoder-only models achieve the best results across tasks, while encoder-decoder models perform better under the same parameter scale. Additionally, the comparison of the performance between fine-tuning and prompt engineering approaches reveals the considerable potential capability of the prompt engineering approach in unit testing tasks. We then discuss the concerned issues on the test generation task, including data leakage issues, bug detection capabilities, and metrics comparisons. Finally, we further pinpoint various practical guidelines for LLM-based approaches to unit testing tasks in the near future. Overall, our work demonstrates the promising future of fine-tuning LLMs on unit testing tasks and reduces the manual efforts of unit testing experts in practical scenarios.

CCS Concepts: • Software and its engineering → Software testing and debugging.

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1 Introduction

Unit testing is a crucial part of the software development lifecycle, significantly enhancing software quality and reliability [46, 58]. It involves the systematic execution of software to detect potential bugs, verify expected behaviors, and ensure compliance with requirements, thereby enhancing developers' efficiency in development and debugging. However, constructing effective test cases manually is both challenging and time-intensive, with studies indicating that developers often spend over 15% of their time on test generation [12]. As a result, automated test generation has gained substantial interest among developers and researchers. Numerous approaches have been proposed to reduce manual effort, including symbolic execution testing [9, 11], model-based testing [13, 32], random testing [29, 34], and search-based testing [8, 17].

A unit test typically includes two components: (1) a test prefix, i.e., a sequence of statements that manipulate the unit under test to a specific state, and (2) a test assertion, i.e., an oracle that defines the conditions that should be satisfied in that state [14]. In the literature, there are mainly three unit testing tasks based on different perspectives: test generation, assertion generation, and test evolution. First, the test generation task takes a focal method (i.e., the method under test) as input and generates a unit test that includes both a test prefix and an assertion to ensure the focal method functions correctly [44]. Second, the assertion generation task focuses on generating meaningful assert statements for a given focal method and a test prefix to capture potential faults effectively. Third, the test evolution task attempts to generate an updated unit test consisting of both prefixes and assertions while incorporating additional inputs, including the original focal method, its unit test, and the updated focal method [25]. The test evolution task is usually conducted during software evolution, where the focal method adapts to meet new requirements or resolve issues, requiring unit tests to co-evolve to maintain software quality. Overall, these three tasks, i.e., test generation, assertion generation, and test evolution, represent distinct aspects of unit testing across various levels of granularity and scenarios, offering a comprehensive view of unit testing.

This Paper. Recently, Large Language Models (LLMs) have demonstrated impressive performance on various code-related tasks such as code generation [26, 50], code summarization [6, 41], and program repair [57, 59]. In the domain of unit testing, several studies have explored LLM-based approaches with promising results. For instance, A3Test [7] fine-tunes a PLBART model specifically for test generation and Zhang et al. [64] explore the capability of several LLMs for assertion generation. Furthermore, CEPROT [25] leverages CodeT5, a pre-trained model designed to learn from source code, to capture semantic correlations effectively in the test evolution task. Despite ongoing research, the literature still lacks a systematic evaluation of LLMs in unit testing, making it difficult for researchers to assess the true capabilities of LLMs in performing various unit testing tasks. To fill this gap, we conduct the first large-scale empirical study on LLMs for unit testing, including three unit testing tasks (i.e., test generation, assertion generation, and test evolution) across 37 LLMs with different architectures (i.e., encoder-only, encoder-decoder, and decoder-only) and size (ranging from 60 million to 16 billion parameters). Our study provides a comprehensive evaluation of LLMs on these common unit testing tasks, facilitating future research in this area. Specifically, we address the following three research questions.

- **Performance of LLMs on Unit Testing Tasks.** In RQ1, we evaluate the performance of LLMs on test generation, assertion generation, and test evolution tasks, comparing them to previous state-of-the-art approaches using two types of metrics. **Results:** LLMs significantly outperform several state-of-the-art approaches such as ATLAS for assertion generation [49], ATHENATEST for test generation [44], and CEPROT for test evolution [25], across nearly all metrics, highlighting their potential in unit testing.
- **Impact of Various Factors on LLMs' Performance.** In RQ2, we evaluate the effects of model series, architecture, and size on LLMs' performance. **Results:** (1) large-scale LLMs consistently outperform smaller ones; (2) decoder-only models achieve the highest performance overall, with encoder-decoder models showing strength at comparable parameter sizes; (3) the CodeLlama [39], DeepSeek-Coder [20], and CodeT5p [47] series models are particularly promising.
- **Comparison between the Fine-tuning and Prompt Engineering Approaches.** In RQ3, we compare the effectiveness of the fine-tuning and prompt engineering approaches across three unit testing tasks. **Results:** prompt engineering approach with zero-shot learning produces promising results in test generation and test evolution tasks, indicating its considerable potential capability in common unit testing tasks.

Novelty & Contributions. To sum up, the main contributions of this paper are as follows:

- **New Dimension.** We bridge the gap between LLMs and three unit testing tasks: test generation, assertion generation, and test evolution. Our study not only provides a comprehensive evaluation of LLMs' performance but also highlights the potential of fine-tuning LLMs in unit testing.
- **Extensive Study.** We conduct the first large-scale empirical study on fine-tuning 37 popular LLMs in three unit testing scenarios across five benchmarks and eight metrics, utilizing over 3,000 NVIDIA A100 GPU hours. Our study includes (1) a systematic comparison of LLMs with state-of-the-art methods for unit testing; (2) an in-depth analysis of factors affecting LLMs' performance; and (3) a complete comparison between fine-tuning and prompt engineering approaches.
- **Practical Guidelines.** Based on our extensive findings, we provide practical guidelines to inform and guide future research and practice in applying LLM-based approaches to unit testing tasks.

2 Background and Related Work

2.1 Test Generation

Unit test generation can be broadly categorized into traditional approaches and Deep Learning (DL)-based approaches. Traditional approaches, exemplified by tools like Evosuite [17] and Randoop [34], utilize a series of software analysis techniques, including search-based [17], random-based [34], model checking [15, 18], and symbolic execution [36, 51], to generate unit tests that achieve high code coverage and mutation scores.

DL-based approaches, by using pre-trained models, treat the test generation task as a neural machine translation problem, where the input primarily consists of the focal methods and the output is the generated unit tests. Tufano et al. [44] introduce an approach named ATHENATEST to generate unit tests, which use a BART architecture model for a two-step training procedure on a large processed dataset. Alagarsamy et al. [7] propose an approach named A3Test. In addition to using a PLBART model, A3Test implements simple post-processing steps such as verifying naming consistency, correcting incomplete parentheses, and refining test signatures to increase the correctness rate. More recently, with the significant impact of closed-source LLMs like ChatGPT, many researchers have explored using a prompt engineering approach to generate unit tests. Yuan et al. [56] propose ChatTester, which combines an initial test generator with an iterative test refiner to produce unit tests. Chen et al. [10] introduce ChatUniTest, which generates unit tests under the Generation-Validation-Repair framework. Gu et al. [19] introduce TestART, a framework that

generates high-quality unit test cases by integrating traditional template-based program repair[62] with the generative capabilities of LLMs within a *generation-and-repair* mechanism. Zhang et al. [63] introduce TestBench, the first benchmark tailored to class-level LLM-based test case generation, involving 108 Java programs from 9 large-scale GitHub projects, three distinct prompt types and five key evaluation aspects of test cases. Besides, some empirical studies [40, 52] have emerged, comparing the effectiveness of different LLMs with various prompt strategies.

2.2 Assertion Generation

Assertion generation is primarily approached using two approaches [21]: DL-based approaches and Information Retrieval (IR)-based approaches. DL-based approaches treat assertion generation as a Neural Machine Translation (NMT) task. Watson et al. [49] pioneer the use of DL-based approaches in assertion generation with their proposal of *ATLAS*. Later, IR-based approaches are applied to the assertion generation task as well, which use retrievers to find similar assertions based on focal-test information and then correct the retrieved assertions by replacing incorrect tokens with the correct ones based on context. Yu et al. [54] propose an IR-based method, introducing IR-based assertion retrieval (IR_{ar}) and retrieved-assertion adaptation (RA_{adapt}) approaches. IR_{ar} retrieves the most similar assertion to the given focal-test, while RA_{adapt} adjusts tokens based on context to refine the assertion. Yu et al. further propose an integrated approach (abbreviated as *Integration*), which comprehensively considers assertions generated by both IR-based and DL-based approaches. Recently, hybrid approaches [42] combining DL-based methods and IR-based methods have been proposed and proven effective. These combined approaches leverage the strengths of both approaches, resulting in more meaningful and useful assertions for developers.

2.3 Test Evolution

Hu et al. [25] first use a DL-based method to generate updated test cases for the test evolution task in CEPROT. CEPROT focuses on the changes (i.e., edit sequences) between two versions of the production code and attempts to transfer these changes to the outdated test code to generate updated test code. Yaraghi et al. [53] propose an approach named TARGET, which employs a two-step process to fine-tune a model based on the dataset. TARGET focuses on repairing outdated test code. The input to the model is not limited to the related production code but also considers potential context from all changes in the project between the two versions. Recently, Liu et al. [27] propose SYNBCIATR, which focuses on syntactic breaking changes and attempts to automatically repair outdated test cases via precise and concise Test-Repair-Oriented Contexts (TROCtx) construction.

2.4 Large Language Models

LLMs are large-scale models pre-trained on massive textual corpora [33, 37, 45], demonstrating strong capabilities across various Natural Language Processing (NLP) tasks [66] and Software Engineering (SE) [46, 60]. LLMs are primarily built on the Transformer [45] architecture, which includes an encoder for input representation and a decoder for output generation. Based on the structure, LLMs can be categorized into three types: (1) encoder-only models (e.g., CodeBERT [16]), designed for understanding tasks; (2) encoder-decoder models (e.g., CodeT5 [48]), designed for translation tasks; and (3) decoder-only models (e.g., CodeGen [31]), designed for generation tasks.

To improve the performance of LLMs on unseen downstream tasks, researchers often fine-tune pre-trained models using task-specific datasets [55, 61]. However, with recent advancements in LLM capabilities, particularly in in-context learning, there is a growing trend towards using prompt engineering as an alternative approach to handling downstream tasks [46]. While commercial LLMs continue to dominate the top of the leaderboards recently, an increasing number of open-source

models, such as CodeLlama [39] and DeepSeek-Coder [20], are emerging and demonstrating strong performance across various tasks.

3 Study Design

3.1 Research Questions

This study aims to answer the following research questions:

RQ1: How does the performance of fine-tuning LLMs compare to existing approaches on three unit testing tasks?

RQ2: What is the impact of various factors (including model series, model architecture, and model size) on the performance of LLMs?

RQ3: How do fine-tuning approaches perform compared to prompt engineering approaches?

3.2 Evaluation Metrics

Following previous studies [25, 44, 49, 54], we focus on two types of metrics: (1) runtime-based metrics, which focus on the correctness and behavior of generated code within execution environments, primarily for test generation tasks; and (2) text-based metrics, which assess the syntactic and semantic accuracy of generated outputs, used for assertion generation and test evolution tasks.

3.2.1 Runtime-based Metrics. We leverage five metrics to evaluate LLMs' performance on the test generation task: syntax error, compilation error, failing test, passing test, and correct test.

- **Syntax Error.** The test has syntax errors.
- **Build Error.** The test has correct syntax but fails to build.
- **Failing Test.** The test builds but fails due to wrong assertions or expected behavior.
- **Passing Test.** The test builds and passes.
- **Correct Test.** The test passes and covers the correct focal method.

3.2.2 Text-based Metrics. We then leverage three widely used textual metrics to evaluate the performance of LLMs on the assertion generation and test evolution tasks.

- **Exact Match Accuracy (EM).** The EM metric [24], also known as perfect accuracy, measures the proportion of correctly predicted outputs that exactly match the ground truth. A prediction is considered correct only if each token in the output sequence matches the ground truth precisely.
- **BLEU.** BLEU [35] is an automatic metric used to evaluate the syntactic similarity between the predicted sequence and the reference sequence. It measures n-gram overlap between the translation and references, incorporating precision and brevity to ensure appropriate length.
- **CodeBLEU.** CodeBLEU [38] is a code-aware variant of BLEU specifically designed for evaluating code synthesis tasks. Unlike BLEU, CodeBLEU incorporates syntactic similarity through Abstract Syntax Tree (AST) information and semantic similarity through data-flow analysis. This makes CodeBLEU particularly effective for assessing the quality of code generation tasks.

3.3 Selected Models

In our selection of LLMs, we evaluate 37 state-of-the-art models based on their architectural complexity and performance on key benchmarks. These models fall into three major architectural categories: encoder-only, encoder-decoder, and decoder-only. Our final selection includes 20 distinct model series (e.g., CodeT5, CodeGen), comprising a total of 37 models, each varying in size and architecture. The sizes of these models range from 60 million parameters (e.g., CodeT5-small) to 16 billion parameters (e.g., CodeGen-16b-multi), allowing us to evaluate models under different

computational constraints while balancing efficiency and task performance. We provide a detailed list of our selected models as shown in Table 1.

Table 1. Selected models in this work.

Architecture	Models
Encoder-only	CodeBERT, GraphCodeBERT, UniXcoder
Encoder-decoder	CodeT5 Series (CodeT5-small, CodeT5-base, CodeT5-large) CodeT5+ Series (CodeT5+ 220m, CodeT5+ 770m) PLBART Series (PLBART-base, PLBART-large)
Decoder-only	CodeGPT, SantaCoder, DeciCoder, CodeShell, InCoder, StarCoder Phi Series (Phi-1, Phi-2) CodeGen Series (CodeGen-350m-multi, CodeGen-2b-multi, CodeGen-6b-multi, CodeGen-16b-multi) CodeGen2 Series (CodeGen2-1b-p, CodeGen2-3.7b-p) StarCoderBase Series (StarCoderBase-1b, StarCoderBase-3b, StarCoderBase-7b, StarCoderBase-15.5b) StarCoder2 Series (StarCoder2-3b, StarCoder2-7b, StarCoder2-15b) CodeLlama Series (CodeLlama-7b, CodeLlama-13b) CodeGenma Series (CodeGenma-2b, CodeGemma-7b) DeepSeek-Coder Series (DeepSeek-Coder-1.3b-base, DeepSeek-Coder-6.7b-base)

For decoder-only LLMs, we represent tasks as auto-regressive generation tasks. Given an initial prompt or source sequence, the decoder model predicts the next token by sampling from the probability distribution $P(t_i|t_1, \dots, t_{i-1})$, where t_1, \dots, t_{i-1} represent all the tokens generated up to position i . This process continues iteratively until the model generates an end-of-sequence token or reaches a predefined length. For encoder-decoder LLMs, we represent tasks as sequence-to-sequence translation tasks. In these models, fine-tuning is performed on a mapped source-target pair, denoted as $mst_i = \{s_i, t_i\}$, where s_i is the source sequence and t_i is the target sequence. The fine-tuning process learns the mapping $s_i \rightarrow t_i$ as a conditional probability $P(t_i|s_i)$. For encoder-only LLMs, we manually extend them into encoder-decoder architectures by integrating a transformer decoder stack and treat them as encoder-decoder LLMs.

After training the LLMs for each task, we apply the beam search strategy when provided with a source sequence. This strategy generates the predicted target sequence by selecting words from multiple candidate sequences based on the probability distribution over the vocabulary.

3.4 Dataset

3.4.1 Test generation task. In the test generation task, we utilize Methods2Test dataset proposed by Tufano et al. [43, 44] to fine-tune LLMs. Methods2Test is a comprehensive, supervised dataset comprising test cases paired with their corresponding focal methods. This dataset is created through an extensive mining process, resulting in 780,944 pairs of JUnit tests and focal methods.

However, due to resource constraints, we are unable to use the entire dataset. To reduce the dataset and enhance its quality, we filter the dataset by following rules. (1) *Length of Tokens*. To ensure data completeness and simplicity, we filter out entries with token lengths that are either too short or too long. Specifically, we retain entries where the length of the input focal method is between 64 and 2048, and the length of the output test case is between 16 and 512. (2) *Construction*. To normalize the construction of test cases, we only retain entries that begin with the prefix ‘@Test public void’ and do not throw exceptions. (3) *Duplicated Test Cases*. We find half of the focal methods in the dataset include at least two related test cases. To increase the variety of focal methods, we randomly select one pair from each set of test cases associated with the same focal methods. (4) *Filtered repository*. To maintain the quality of the dataset, we filter out any repository

with fewer than 50 pairs. Conversely, to ensure a diverse set of test cases that are not dominated by a few repositories, we randomly sample 200 pairs from any repository with more than 200 pairs.

Applying the above rules to the dataset, we obtain 56,132 pairs of data and call this dataset *Method2Testfilter*. We then split the filtered dataset by repositories into training, validation, and test sets using an 8:1:1 ratio for further fine-tuning.

Furthermore, previous works [7, 30, 44] primarily adopt runtime-based metrics to evaluate the performance of test generation approaches, focusing on the correct test rate. Similar to ATHEN-ATEST [44], we employ Defects4J as our benchmark dataset to evaluate LLMs’ performance and use the same five evaluated projects: Apache Common Cli [1], Apache Common Csv [2], Google Gson [4], JFreeChart [5] and Apache Commons Lang [3]. These projects cover various domains, such as command-line interfaces, data processing, serialization, visualization, and utilities.

3.4.2 Assertion generation task. In the assertion generation task, we use the dataset known as *Data_{old}*. This dataset is derived from a raw dataset used by ATLAS [49]. Each entry in *Data_{old}* is referred to as a Test-Assert Pair (TAP). A TAP consists of two components: (1) a focal-test pair, which includes a test method without an assertion and its corresponding focal method; (2) assertions. To simplify the problem, *Data_{old}* excludes any TAP where the assertions contain tokens that are not present in the focal-test pair. In total, *Data_{old}* contains 156,760 TAPs, which are divided into training, validation, and test sets by the ratio of 8:1:1 for further fine-tuning.

3.4.3 Test evolution task. In the test evolution task, we utilize the dataset proposed by Hu et al. [25]. Specifically for the obsolete test updating task mentioned in the paper. Each sample in the dataset consists of <*original method, updated method, original test, updated test*>. The dataset contains 5,196 samples, which the authors originally split into training and test sets using a 9:1 ratio. We further create a validation set by randomly selecting 11% of the samples from the training set, resulting in a final split ratio of 8:1:1 for the training, validation and test sets.

3.5 Implementation Details

We implement all model training approaches using the PyTorch framework. For the studied models, we use the Hugging Face versions. For model training, we adopt the default training parameters from previous studies for each task. However, due to the variety of models and tasks, we specifically adjust some training parameters. We use the AdamW optimizer with a learning rate of 5e-5 and train for a maximum of 50 epochs for all tasks. Additionally, we apply early stopping with a patience of two epochs, meaning training halts if the loss does not decrease for two consecutive epochs. Maximum input and output sequence lengths are adjusted according to task-specific and model-specific requirements. For the assertion generation and test evolution tasks, we set source and target sequence lengths to 512 and 256, respectively. For the test generation task, we use lengths of 2048 and 512 due to the long context information.

We conduct our experiments on a computing cluster with several A100 nodes (8x NVIDIA A100-PCIE-40GB). We utilize DeepSpeed to accelerate training and reduce memory usage.

4 Result and Analysis

4.1 RQ1: Performance of LLMs on Unit Testing Tasks

Motivation. Existing researches [25, 44, 53] on unit testing tasks often utilize models smaller than 1 billion parameters, such as CodeBERT, CodeT5 and CodeGPT. Due to the limited size and number of models, these studies often lack comprehensive analysis of specific tasks. In this RQ, we aim to

provide a comprehensive evaluation of LLMs' performance on three unit testing tasks. Due to the large number of LLMs, we focus our analysis on selecting representative models for each task¹.

4.1.1 Test Generation. Design. In the test generation task, we compare the performance of LLMs with four state-of-the-art test generation approaches from previous research: ATHENATEST [44], A3Test [7], ChatUniTest [10], and CasModaTest *GPT3.5* [30]. The evaluation uses five runtime-based metrics, primarily focusing on the correct test rate. Notably, due to resource constraints, we do not fine-tune several large-scale models in the test generation task.

Table 2. Comparisons of LLMs with previous approaches on the test generation task using the Defects4J dataset. The best results among all LLMs are **bolded**, and the second-best results are underlined.

Approaches/LLMs	Correct	Passing	Failing	Build Error	Syntax Error
ATHENATEST	16.21%	21.35%	26.71%	42.41%	9.49%
A3Test	40.05%	-	-	-	-
ChatUniTest	40.14%	-	-	-	-
CasModaTest <i>GPT3.5</i>	77.16%	-	-	-	-
CodeBERT	5.56%	8.41%	5.99%	78.90%	6.70%
GraphCodeBERT	11.77%	14.02%	11.19%	65.89%	8.89%
UniXcoder	6.42%	8.12%	10.48%	69.02%	12.37%
CodeT5-base	15.91%	18.76%	14.90%	61.36%	<u>4.98%</u>
CodeT5p-220m	17.75%	19.79%	27.07%	50.26%	2.88%
PLBART-large	17.50%	20.25%	20.63%	52.96%	6.16%
CodeGPT	7.66%	9.64%	9.81%	39.67%	40.88%
StarCoder2-7b	20.78%	23.10%	23.16%	41.45%	12.30%
CodeLlama-7b	<u>29.50%</u>	<u>32.14%</u>	<u>7.86%</u>	<u>30.87%</u>	29.13%
DeepSeek-Coder-6b	33.68%	36.02%	9.00%	21.36%	33.62%

Result. Table 2 presents the comparison of LLMs and the four state-of-the-art approaches on the test generation task. We classify prior approaches into two categories: the first primarily leverages fine-tuning strategies for adapting models to the test generation task (e.g., ATHENATEST and A3Test); the second employs prompt engineering based approaches to guide LLM behavior toward desired outputs without modifying model weights (e.g., ChatUniTest and CasModaTest *GPT3.5*, which predominantly uses GPT-3.5 as the underlying model).

Compared to ATHENATEST, the encoder-only models (e.g., CodeBERT, GraphCodeBERT, and UniXcoder) underperform across correct, passing, and build error rates. Among these, GraphCodeBERT performs the best but still shows a 27.39% reduction in the correct test rate and a 55.36% increase in the build error rate compared to ATHENATEST. The encoder-decoder models (e.g., CodeT5-base, CodeT5p-220m, and PLBART-large) perform similarly to ATHENATEST, while the decoder-only models generally achieve better results. The best-performing decoder-only model, DeepSeek-Coder-6b, reaches a correct rate of 33.68%, which is 107.77% higher than ATHENATEST, and has a build error rate of 21.36%, 49.63% lower than ATHENATEST.

Despite their strong performance in correct test rates, decoder-only models exhibit higher syntax error rates. A manual analysis of the generated test cases marked with syntax errors reveals that these cases typically involve long contexts that exceed the models' context window. For example, CodeGPT exhibits the highest syntax error rate, which can be attributed to its shorter context window of 1024 tokens compared to the 2048 tokens in other decoder-only models. To address this, we truncate the input context to leave enough space for the models to generate test cases.

¹Complete comparison of LLMs is presented in our repository due to page limit.

However, due to the auto-regressive fine-tuning objective, the models may attempt to complete the truncated input sequence rather than focus on generating the test case, even with adding the end-of-sequence (eos) token. In contrast, models with other architecture are less prone to this issue, likely due to the separation of tasks between the encoder and decoder components, which provides better handling of input context.

When compared to A3Test, all LLMs show inferior performance. This is primarily due to A3Test incorporating additional post-processing verification components. In addition, prompt engineering-based approaches like ChatUniTest and CasModaTest _{GPT3.5} achieve higher correct test rates. Notably, CasModaTest _{GPT3.5} reaches a 77.16% correct rate, which is 129.10% higher than DeepSeek-Coder-6b. These results suggest two points: first, the fine-tuning approach can be improved by a well-designed post-process. Second, with effective task segmentation, prompt construction, and a robust feedback mechanism, prompt engineering approaches can deliver exceptional performance.

Finding 1: Although LLMs demonstrate improvements over ATHENATEST, they underperform compared to A3Test and the two prompt engineering-based approaches. The results suggest that fine-tuning alone is insufficient to achieve state-of-the-art performance in the test generation task, and well-designed post-processing steps are also critical.

4.1.2 Assertion Generation. Design. In the assertion generation task, we compare the performance of LLMs with six state-of-the-art assertion generation approaches from prior researches [42, 49, 54]: *ATLAS*, *IR_{ar}*, *RA_{adapt}^H*, *RA_{adapt}^{NN}*, *Integration*, and *EDITAS*, using three text-based metrics. Notably, due to resource constraints, we do not fine-tune several large-scale models.

Result. Table 3 compares LLMs with state-of-the-art approaches on the assertion generation task. We first compare the performance of the LLMs with the most relevant baseline approach, *ATLAS*, which also frames the assertion generation problem as a neural machine translation task, similar to the LLMs. On the *Data_{old}* dataset, the LLMs achieve prediction EMs ranging from 50.53% to 71.42%, representing an improvement of 60.82% to 127.33% over *ATLAS*. Additionally, LLMs achieve the highest BLEU and CodeBLEU scores of 85.89% and 88.25%, respectively, which are improvements of 25.37% and 38.76%, over *ATLAS*. These significant improvements suggest that LLMs have a distinct advantage in assertion generation task when compared to the default transformer model.

Table 3. Comparisons of LLMs with previous approaches on the assertion generation task using the *Data_{old}* dataset. The best results among all LLMs are **bolded**, and the second-best results are underlined.

Approaches/LLMs	EM	BLEU	CodeBLEU
<i>ATLAS</i>	31.42%	68.51%	63.60%
<i>IR_{ar}</i>	36.26%	71.49%	71.03%
<i>RA_{adapt}^H</i>	40.97%	73.28%	72.46%
<i>RA_{adapt}^{NN}</i>	43.63%	73.95%	72.12%
<i>Intergration</i>	46.54%	78.86%	73.29%
<i>EDITAS</i>	53.46%	80.77%	77.00%
CodeBERT	54.64%	74.31%	73.89%
GraphCodeBERT	58.32%	74.69%	76.02%
UniXcoder	55.12%	68.92%	73.14%
CodeT5-base	60.26%	<u>85.12%</u>	<u>87.32%</u>
CodeT5p-220m	61.76%	85.89%	88.25%
PLBART-base	53.92%	82.09%	84.86%
CodeGPT	51.30%	61.28%	69.12%
StarCoder-2-3b	63.29%	72.50%	77.60%
CodeLlama-7b	71.42%	83.92%	83.34%
DeepSeek-Coder-6b	70.57%	82.99%	82.66%

When compared to four retrieval-based approaches (i.e., *IR_{ar}*, *RA_{adapt}^H*, *RA_{adapt}^{NN}*, and *intergration*), LLMs still demonstrate a clear advantage. We compare the best EM, BLEU, and CodeBLEU scores achieved by LLMs, 71.42%, 85.89%, and 88.25%, respectively, to those achieved by the *intergration* approach, which performs best among four approaches. LLMs show improvements of 53.46% in EM, 8.91% in BLEU and 20.41% in CodeBLEU. Even when compared to the most recent retrieval-enhanced learning-based approach, *EDITAS*, LLMs still outperform, with improvements of 33.60% in EM, 6.34% in BLEU and 14.61% in CodeBLEU. This further confirms the superiority of LLMs in the assertion generation task.

Additionally, we observe that while previous state-of-the-art approaches typically achieve

LLMs' pre-training phase, which enhances their understanding of code structure and boosts their performance on code-related tasks.

Finding 2: Compared to existing state-of-the-art approaches, LLMs demonstrate significant improvements across all three text-based metrics. Notably, LLMs tend to achieve higher CodeBLEU scores than BLEU scores, which is opposite of the trend observed in previous approaches, suggesting that LLMs have a better understanding of code structure.

4.1.3 Test Evolution. Design. In the test evolution task, we compare the performance of LLMs against the CEPROT [25] approach and two traditional machine learning methods, KNN and NMT, using three text-based metrics.

Result. Table 4 compares LLMs and three approaches on the test evolution task, showing that LLMs consistently outperform the two machine learning methods, KNN and NMT. The prediction EM for LLMs ranges from 6.15% to 35.58%, showing a substantial improvement of 23.0% to 611.6% over NMT. For the CodeBLEU metric, LLMs achieve scores ranging from 46.42% to 86.35%, marking an improvement of 23.46% to 129.65% over KNN. These results highlight that LLM-based methods significantly outperform traditional machine learning approaches in the test evolution task.

Table 4. Comparisons of LLMs with previous approaches on the test evolution task. The best results among all LLMs are **bolded**, and the second-best results are underlined.

Apporaches/LLMs	EM	BLEU	CodeBLEU
KNN	3.9%	-	37.6%
NMT	5.0%	-	32.3%
CEPROT	12.3%	-	63.1%
CodeBERT	6.15%	37.72%	46.42%
GraphCodeBERT	12.69%	63.49%	67.37%
UniXcoder	10.58%	58.03%	63.12%
CodeT5-base	12.88%	78.31%	78.31%
CodeT5p-220m	17.12%	81.54%	81.54%
PLBART-base	12.88%	77.88%	78.45%
CodeGPT	15.38%	79.77%	81.58%
StarCoder2-15b	29.04%	83.45%	84.71%
CodeLlama-13b	<u>34.62%</u>	85.20%	86.13%
DeepSeek-Coder-6b	35.58%	<u>84.48%</u>	86.35%

its base model, we compare the performance of the standalone CodeT5-base model directly with CEPROT. The standalone CodeT5-base model achieves 12.88% in EM and 78.31% in CodeBLEU, showing an improvement of 4.7% in EM and 24.1% in CodeBLEU compared to CEPROT. This indicates that reallocating space from the edit sequence to other content improves the LLMs' performance, particularly in terms of the CodeBLEU score.

higher BLEU scores than CodeBLEU scores, LLMs often exhibit the opposite trend, producing higher CodeBLEU scores compared to BLEU. This discrepancy may be due to the extensive code-related corpus used during the

LLMs' pre-training phase, which enhances their understanding of code structure and boosts their performance on code-related tasks.

We then compare the performance of LLMs with the CEPROT approach. Interestingly, we observe a similar situation as in the test generation task. The encoder-only models perform the worst, while encoder-decoder models achieve results similar to CEPROT, and decoder-only models generally perform better. The top-performing model, DeepSeek-Coder-6b, achieves 35.58% EM and 86.35% CodeBLEU, representing improvements of 189.27% and 36.85%, respectively. Furthermore, as described in Section 3.5, we use a tuple containing the original method, the updated method, and the original test as model inputs, thereby removing the edit sequence compared to CEPROT. We find that the edit sequence is too long to be fully incorporated into the input vector, and truncating it typically results in the loss of valuable information, leading us to remove the edit sequence entirely. Since CEPROT also utilizes CodeT5 as

Finding 3: Overall, all LLMs outperform traditional ML-based methods, and most LLMs also surpass the performance of CEPROT. Furthermore, comparing CodeT5-base and CEPROT suggests that reallocating space from the edit sequence to other content can improve performance.

4.2 RQ2: Impact of Various Factors on LLMs' Performance

Motivation. In addition to evaluating specific LLMs, we are also interested in identifying the key factors of high-performing LLMs. Our analysis is based on three factors: model series, model architecture, and model size. In this RQ, we aim to determine how each of these factors influences the performance of LLMs. The model series groups models within the same series into one category, as shown in Section 3.3. For instance, the CodeT5 series includes CodeT5-small, CodeT5-base, and CodeT5-large. Model architecture refers to three types: encoder-only, encoder-decoder, and decoder-only. Model size pertains to the number of parameters in each model, which in our study ranges from 60 million to 16 billion.

4.2.1 The Impact of Model Series. Design. In this section, we explore the performance of different model series by analyzing 17 different representative model series across three unit testing tasks.

Table 5. Performane of different series LLMs across three tasks. The best results among all LLMs are highlighted in **bold**, and the second-best results are underlined.

LLMs	Test Generation					Assertion Generation			Test Evolution		
	Correct	Passing	Failing	Build Error	Syntax Error	EM	BLEU	CodeBLEU	EM	BLEU	CodeBLEU
CodeBERT	5.56%	8.41%	5.99%	78.90%	6.70%	54.64%	74.31%	73.89%	6.15%	37.72%	46.42%
GraphCodeBERT	11.77%	14.02%	11.19%	65.89%	8.89%	58.32%	74.69%	76.02%	12.69%	63.49%	67.37%
UniXcoder	6.42%	8.12%	10.48%	69.02%	12.37%	55.12%	68.92%	73.14%	10.58%	58.03%	63.12%
CodeT5	16.63%	18.95%	20.02%	57.30%	3.73%	58.57%	<u>84.22%</u>	<u>86.67%</u>	12.76%	76.55%	76.75%
CodeT5p	15.94%	18.64%	24.69%	51.25%	<u>5.44%</u>	61.02%	85.47%	87.67%	19.52%	79.31%	80.43%
PLBART	14.96%	16.96%	16.82%	59.51%	6.71%	54.51%	82.31%	85.01%	14.04%	77.84%	78.56%
CodeGPT	7.66%	9.64%	9.81%	39.67%	40.88%	51.30%	61.28%	69.12%	15.38%	79.77%	81.58%
InCoder	17.50%	19.32%	21.56%	50.73%	8.39%	62.24%	77.17%	75.50%	26.15%	79.95%	83.41%
CodeGen	16.80%	19.24%	11.92%	37.24%	31.60%	62.53%	75.59%	77.05%	27.93%	81.97%	83.17%
CodeGen2	-	-	-	-	-	62.74%	74.40%	77.02%	<u>28.56%</u>	83.31%	84.72%
StarCodeBase	27.82%	<u>31.02%</u>	14.65%	34.69%	19.64%	65.24%	76.50%	79.35%	<u>28.56%</u>	81.74%	83.82%
StarCode2	21.22%	23.74%	21.10%	42.15%	13.02%	64.03%	75.40%	78.16%	24.55%	81.16%	83.16%
Phi	14.77%	19.51%	12.04%	53.85%	14.61%	55.37%	67.78%	72.34%	18.56%	79.79%	80.29%
CodeLlama	29.50%	32.14%	7.86%	<u>30.87%</u>	29.13%	71.42%	83.92%	83.34%	34.62%	83.21%	85.33%
CodeGemma	22.84%	25.50%	15.03%	50.37%	9.10%	61.06%	74.26%	77.79%	27.88%	84.34%	85.06%
DeepSeekCoder	25.63%	29.20%	11.03%	28.78%	31.00%	68.10%	81.46%	81.23%	34.62%	<u>84.19%</u>	86.05%
SantaCoder	11.55%	15.44%	<u>7.38%</u>	39.33%	37.85%	57.60%	73.44%	74.66%	27.12%	82.46%	83.85%

Result. Table 5 demonstrates the performance of different series of LLMs across three unit testing tasks. We calculate the average score of a LLM series to represent the performance of this LLM series. According to Table 5, CodeLlama leads in performance, achieving the highest EM scores in both the assertion generation (71.42%) and test evolution (34.62%) tasks, as well as the highest correct test and passing rates in the test generation task, 29.50% and 32.14%, respectively. DeepSeek-Coder and StarCodeBase also perform well: DeepSeek-Coder ranks second in EM for assertion generation (68.10%) and tops the test evolution task in EM and CodeBLEU scores (34.62%). StarCodeBase achieves strong results in test generation, with the second-highest correct test rate at 27.82% and the passing rate at 31.02%, as well as a high EM score at 28.56% in test evolution. CodeT5p and CodeT5 series models excel in BLEU and CodeBLEU scores in assertion generation.

On the other hand, CodeBERT performs the worst across tasks, with the lowest correct test rate at 5.56%, the passing rate at 8.41%, and the highest build error rate at 78.90% in the test generation task. It also has the lowest EM, BLEU, and CodeBLEU scores in the test evolution task, 6.15%, 37.72%, and 46.42%, respectively. Similarly, CodeGPT has the lowest EM, BLEU, and CodeBLEU scores for

assertion generation, 51.30%, 61.28%, and 69.12%, respectively, and the highest syntax error rate in the test generation task.

Finding 4: CodeLlama outperforms other models across all tasks, with the highest EM, correct test rate, and passing rate. DeepSeekCoder and StarCodeBase also show strong performance, particularly in assertion generation and test generation tasks. In contrast, CodeBERT and CodeGPT consistently perform the worst, with low EM and high error rates.

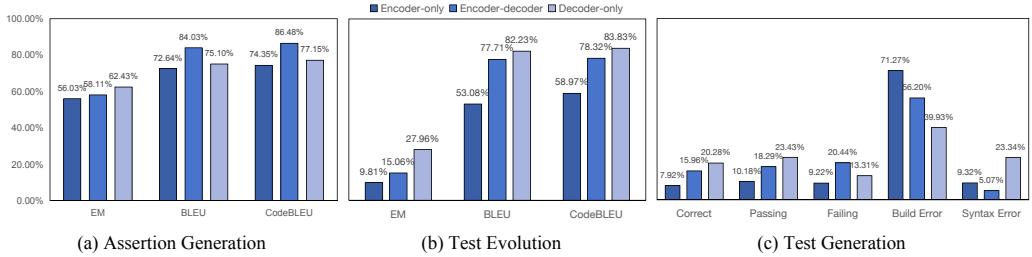


Fig. 1. Performance of LLMs with different architectures across three tasks.

4.2.2 The Impact of Model Architecture Design. In this section, we examine how model architecture influences performance. To provide a clearer comparison across architectures, we calculate the average metrics for each architecture.

Result. Fig. 1 shows the performance of LLMs with different architectures across three tasks. In the assertion generation task, decoder-only models achieve the highest average EM score at 62.43%, followed by encoder-decoder models at 58.11% and encoder-only models at 56.03%. However, when considering BLEU and CodeBLEU scores, encoder-decoder models outperform others with an average BLEU of 84.03% and CodeBLEU of 86.48%. Decoder-only models perform less well, with BLEU at 72.64% and CodeBLEU at 74.35%. In the test evolution task, the EM scores follow a similar pattern as assertion generation, with decoder-only models leading at 27.96%. Unlike assertion generation, decoder-only models also outperform BLEU and CodeBLEU, with averages of 82.23% and 83.83%, respectively. Encoder-decoder models lag behind with lower EM (15.05%), BLEU (77.71%), and CodeBLEU (78.32%), while encoder-only models perform the worst across all metrics. In the test generation task, decoder-only models achieve the highest correct test rate (20.28%) and passing rate (23.43%), alongside the lowest build error rate (39.93%). This suggests that decoder-only models generate more correct test cases than the other architectures. Encoder-decoder models perform moderately, while encoder-only models perform the worst. However, when it comes to syntax error rates, decoder-only models exhibit the highest error rate at 23.34%, significantly higher than the other two architectures. We speculate that this is due to the auto-regressive objective of decoder-only models analyzed in Section 4.1.1, which may lead them to complete truncated input sequences rather than focus on generating the test case, resulting in higher syntax errors.

Finding 5: Decoder-only models generally perform best across all three tasks, particularly in EM and correctness metrics, but they exhibit higher syntax error rates than the other two architecture models. Encoder-decoder models excel in BLEU and CodeBLEU scores on the assertion generation task, while encoder-only models consistently underperform across all tasks.

4.2.3 The Impact of Model Size. Design. In this section, we explore how model size influences performance across three tasks. We collect the parameter sizes of LLMs and list them on the scatter plot for further analysis.

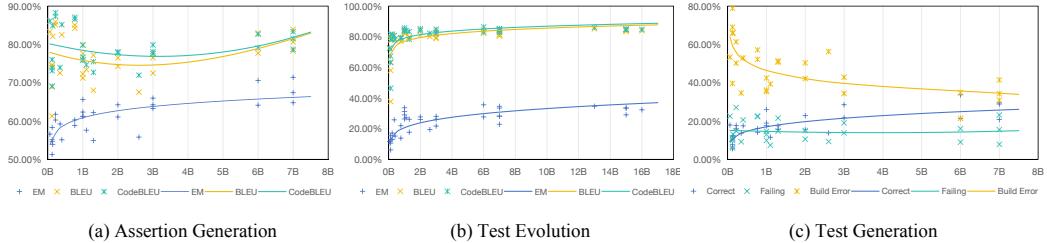


Fig. 2. Performance of LLMs with different sizes across three tasks.

Result. Fig. 2 presents scatter plots of model performance in relation to parameter size, with trend lines added for clarity. In the assertion generation task, the EM score increases as the model size grows, following a pattern of rapid improvement initially, followed by slower gains. BLEU and CodeBLEU scores show a different pattern, first decreasing and then increasing as the size grows, influenced by the strong performance of CodeT5 and CodeT5p models. In the test evolution task, all three metrics—EM, BLEU, and CodeBLEU—improve with increasing model size, again showing rapid early improvement that slows as size increases, indicating a clear positive correlation between size and performance. In the test generation task, the correct test rate increases with model size while the build error rate decreases, suggesting that larger models tend to produce more accurate test cases with fewer build errors. However, the failing rate does not significantly decrease, indicating that even with larger models, many generated test cases still fail to pass.

Finding 6: Large-scale models generally perform better across all tasks, with improved metrics like EM, correct test rate, and reduced build error rates. However, even as model size increases, the failing rate remains high, suggesting that test cases often fail regardless of model size.

4.3 RQ3: Comparison between the Fine-tuning and Prompt Engineering Approaches

Motivation. Recently, with the development of LLMs such as ChatGPT, there is a growing trend towards using prompt engineering as an alternative approach to handling downstream tasks [46]. Unlike fine-tuning LLMs with specific downstream datasets, prompt engineering focuses on designing advanced prompts that incorporate task-specific information, aiming to leverage the existing knowledge within the LLM to solve the problem.

Design. In this RQ, we aim to evaluate and compare the effectiveness of fine-tuning and prompt engineering approaches across three unit testing tasks. We examine six widely used instruction-based LLMs (open and closed-sourced), including GPT-3.5-Turbo, Llama3.1-8b, Llama3.1-70b, Llama3-8b, Qwen2-7b, and Qwen2-72b. For open-source models, we select the instruction-tuned versions to support prompt-based testing. Additionally, We apply the same input data across models and adopt a zero-shot learning setup for prompt construction². Considering that instruction-based LLMs are not explicitly trained for specific downstream tasks, their generated outputs may deviate in format from the ground truth. To address this, we implement two strategies. First, we design structured prompts to guide the model toward desired output formats. Second, we apply post-processing steps to further refine the output. For tasks like assertion generation and test

²Detailed prompt template is presented in our repository due to page limit.

evolution, which are evaluated using text-based metrics, we extract the code output from the model’s response as the predicted output. Then, we use a BERT tokenizer to tokenize both the predicted output and the ground truth, followed by detokenization to standardize formatting. This process unifies delimiters such as whitespace and line breaks and removes special code structures, allowing us to focus purely on semantic content. For test generation tasks, which are evaluated using runtime-based metrics, we also extract the code output from the model response but limit it to the first unit test case. Since the fine-tuning approach generates one test case per focal method, this selective extraction ensures a fair comparison by aligning the number of generated test cases between the two approaches.

Table 6. Comparison between fine-tuning and prompt engineering approaches across three tasks. The best results among all LLMs are **bolded**, and the second-best results are underlined.

LLMs	Test Generation					Assertion Generation			Test Evolution		
	Correct	Passing	Failing	Build Error	Syntax Error	EM	BLEU	CodeBLEU	EM	BLEU	CodeBLEU
CodeT5p-220m	17.75%	19.79%	27.07%	50.26%	2.88%	61.76%	85.89%	88.25%	17.12%	81.54%	81.54%
CodeLlama-7b	29.50%	32.14%	7.86%	<u>30.87%</u>	29.13%	71.42%	<u>83.92%</u>	83.34%	<u>34.62%</u>	81.22%	<u>84.52%</u>
DeepSeek-Coder-6b	33.68%	36.02%	9.00%	21.36%	33.62%	70.57%	82.99%	82.66%	35.58%	<u>84.48%</u>	86.35%
GPT-3.5	49.16%	51.03%	11.33%	34.44%	3.20%	2.97%	32.41%	25.73%	15.96%	86.20%	83.61%
Llama3.1-8b	30.34%	35.04%	10.22%	53.99%	0.75%	0.22%	20.93%	19.46%	4.23%	59.64%	65.25%
Llama3.1-70b	31.02%	33.38%	<u>7.99%</u>	58.09%	0.54%	3.89%	31.58%	27.46%	5.39%	58.40%	63.37%
Llama3-8b	<u>36.88%</u>	<u>38.73%</u>	16.98%	43.60%	<u>0.69%</u>	0.14%	11.49%	18.10%	5.96%	71.16%	76.29%
Qwen2-7b	16.54%	21.39%	18.93%	57.51%	2.17%	0.91%	10.17%	22.49%	0.19%	42.70%	51.07%
Qwen2-72b	29.48%	31.13%	21.81%	45.60%	1.46%	4.89%	27.31%	27.46%	3.46%	54.67%	62.18%

Result. Table 6 presents a performance comparison between fine-tuned models and instruction-based models. For clarity, we focus on three representative fine-tuned models: CodeT5p-220m, CodeLlama-7b, and DeepSeek-Coder-6b. In the test generation task, GPT-3.5 achieves a correct rate of 49.16% and a passing rate of 51.03%, surpassing the best-fine-tuned model, DeepSeek-Coder-6b, which achieves 45.96% and 41.67%, respectively. This suggests promising potential for instruction-based LLMs in test generation tasks. In the assertion generation task, however, instruction-based models underperform, with an EM score of only 4.89%, significantly lower than that of fine-tuned models. BLEU and CodeBLEU scores also lag; even the best-performing instruction model, GPT-3.5, reaches only 32.41% on BLEU and 25.73% on CodeBLEU. We manually analyze the predicted outputs from instruction-based models and observe a tendency to omit fully qualified names, likely because the model assumes that all necessary imports are included. For instance, the prediction might generate ‘assertNull(test)’, while the ground truth specifies ‘org.junit.Assert.assertNull(test)’, contributing to lower performance scores. In the test evolution task, instruction-based models show a wide performance range, with EM scores spanning 0.19% to 15.96%, BLEU from 42.70% to 86.20%, and CodeBLEU from 51.07% to 83.61%. Although instruction-based models perform poorly on EM compared to fine-tuned models, they demonstrate promising BLEU and CodeBLEU scores. Notably, GPT-3.5 achieves the highest BLEU score at 86.20% and ranks top in CodeBLEU at 83.61%.

Additionally, all the instruction-based models perform a low syntax error rate range from 0.54% to 3.2%, showing a promising understanding of code structure. And GPT-3.5 consistently achieves the best overall results, ranking first in seven metrics among the six models. The results of the prompt engineering approach demonstrate its potential in unit test-related tasks. Notably, this study employs only zero-shot learning to construct prompts and generate model responses. Recently, however, advanced in-context learning techniques, such as few-shot learning, Chain of Thought (CoT), and Retrieval Augmented Generation (RAG), have emerged, enhancing LLMs’ capacity

to produce accurate responses. Leveraging these advanced techniques could enable the prompt engineering approach to perform even better in common unit testing tasks.

Finding 7: In summary, the prompt engineering approach shows promising results compared to the fine-tuning approach, particularly in test generation and test evolution tasks, highlighting its potential in unit test-related tasks. Leveraging advanced in-context learning methods, like few-shot learning, CoT, and RAG, could further enhance its performance.

5 Discussion

5.1 Discussion of Potential Data Leakage

The issue of data leakage, as discussed by Zhang et al. [65], poses a critical risk to the evaluation of LLMs in the SE community. In this section, we concentrate on the test generation task, for which we employ Defects4J as an evaluation dataset. To mitigate potential data leakage risk, we test LLMs' performance on a real-world industrial dataset³. Unlike Defects4J, which partially relies on JUnit 3, the internal dataset adopts a unified Maven architecture with the JUnit 4 testing framework. This setup aligns with mainstream development practices and provides a more accurate measure of LLMs' capability to generate test cases for contemporary Java projects.

Table 7. Performance of different LLMs on the internal dataset. The best results among all LLMs are **bolded**, and the second-best results are underlined.

LLMs	Correct	Passing	Failing	Build Error	Syntax Error
UniXcoder	5.39%	6.59%	1.95%	74.10%	17.37%
CodeT5-large	14.07%	16.32%	10.03%	<u>66.77%</u>	6.89%
CodeT5p-770m	18.56%	19.61%	5.54%	71.11%	<u>3.74%</u>
DeepSeek-Coder-6b	31.14%	31.59%	2.84%	29.64%	35.93%
CodeLlama-7b	25.00%	25.45%	<u>2.10%</u>	34.28%	38.17%
StarCoder2-7b	23.05%	24.40%	6.59%	42.66%	26.35%
StarCoderBase-7b	23.65%	27.10%	2.40%	42.96%	27.54%
CodeGen-6b	23.50%	23.95%	<u>2.10%</u>	35.78%	38.17%
GPT-3.5	52.54%	54.34%	12.43%	<u>32.04%</u>	1.20%
Llama3.1-8b	21.71%	22.01%	17.96%	51.50%	8.53%
Llama3.1-70b	<u>51.35%</u>	<u>52.40%</u>	10.48%	32.63%	4.49%
Llama3-8b	28.44%	29.94%	10.33%	54.34%	5.39%
Qwen2-7b	32.34%	32.49%	10.03%	50.90%	6.59%
Qwen2-72b	42.37%	44.61%	7.63%	42.37%	5.39%

Table 7 presents the performance of LLMs on the internal dataset. For simplicity, we select several representative models from both fine-tuned and instruction-based models that perform well on Defects4J dataset. Among fine-tuned models, DeepSeek-Coder-6b achieves the highest performance with a correct rate of 31.14% and the lowest build error rate of 29.64%. The encoder-only model UniXcoder performs the lowest, with a correct rate of only 5.39%, while encoder-decoder models like CodeT5-large and CodeT5p-770m have the lowest syntax error rate at 6.89% and 3.74%, respectively. Overall, results on the internal dataset for fine-tuned models closely align with their performance on Defects4J. In instruction-based models, GPT-3.5 achieves the best results, ranking highest in correct rate, passing rate, and syntax error rate, at 52.54%, 54.34%, and 1.20%, respectively. Llama3.1-70b

³Due to the confidential policy of the company, we hide the information of internal subjects.

and Qwen2-72b generally perform well, occupying second and third places across metrics, with Llama3.1-70b achieving a correct rate of 51.35% and Qwen2-72b at 42.37%.

Instruction-based models generally achieve higher correct rates and lower syntax error rates than fine-tuned models, especially when the model size exceeds 70 billion parameters, showing trends similar to Defects4J dataset. For clarity, we analyze three model groups: (1) fine-tuned models around 7 billion parameters (e.g., DeepSeek-Coder-6b, CodeLlama-7b, StarCoder2-7b, StarCoderBase-7b, CodeGen-6b), (2) instruction-based models around 7 billion parameters (e.g., Llama3.1-8b, Llama3-8b, Qwen2-7b), and (3) instruction-based models exceeding 70 billion parameters (e.g., GPT-3.5, Llama3.1-70b, Qwen2-72b). First, the 7-billion-parameter fine-tuned models achieve correct rates between 23.05% and 31.14%, averaging 25.27%. Second, the 7-billion-parameter instruction-based models show a modest improvement, with correct rates between 21.71% and 32.34% and an average of 27.50%, marking an 8.82% increase. Third, instruction-based models with over 70 billion parameters achieve correct rates between 42.37% and 52.54%, with an average of 48.75%, reflecting substantial improvements of 92.92% over the 7-billion fine-tuned models and 77.27% over the 7-billion instruction-based models.

Overall, these results highlight two main insights. First, among models with similar parameter counts, the performance gap between fine-tuned and instruction-based models is relatively modest. Second, as instruction-based models grow in size and capability, the prompt engineering approach shows strong potential to achieve even higher performance levels.

Summary: While large-scale instruction-based models outperform fine-tuned models overall, instruction-based models with the same parameters scale show slight gains over fine-tuned counterparts. Instruction-based models show promise as they scale in size and capability.

5.2 Discussion of Bug Detection Capability

Evaluating the bug detection capability of generated test cases is essential for understanding their practical effectiveness in real-world development. This section evaluates the ability of generated test cases to detect bugs within a program. To do this, we select several representative models and run their generated test cases on both buggy and fixed versions of five projects aforementioned. Following the previous works [14, 22, 23, 28], the generated tests can be divided into four groups based on the execution results: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Here, Positive indicates that a test case fails on the buggy program, while Negative means it passes on the buggy version. True or False further specifies whether the test case correctly or incorrectly passes/fails on the fixed version. A test is considered as a bug-finding test if it fails on the buggy program but passes on the fixed version. We assess each model's effectiveness and usability by calculating both the number of bugs found and the precision of the test cases. Precision is defined as $\#TP / (\#FP + \#TP)$, representing the proportion of generated test cases that successfully identify bugs among all failing test cases. A higher precision indicates fewer irrelevant test cases, reducing the validation effort required from developers.

Table 8 presents the bug detection performance of generated test cases on Defects4J. Overall, most models perform poorly, typically identifying zero or only one bug. Precision rates are similarly low, ranging from 0.00% to 0.74%, indicating that most LLM-generated test cases fail to detect bugs. The best-performing model, DeepSeek-Coder-6b, identifies 8 out of 163 bugs across five projects, achieving a precision of 0.74%. This means that, even in the best case, a developer must review approximately 135 failing tests to find a single bug. Further analysis of FP samples reveals that build errors account for 69.24% to 92.94% of all failing test cases, which is the primary reason for these failures. These findings suggest that simply generating test cases through fine-tuning alone

Table 8. The performance of LLMs for bug-detection on Defects4J

Model	BugFound	Precision	#TP	#FP
CodeBERT	0	0.00%	0	4535
GraphCodeBERT	1	0.02%	1	4118
UniXcoder	0	0.00%	0	4247
CodeT5-base	4	0.16%	7	4262
CodeT5p-220m	1	0.02%	1	4131
PLBART-large	1	0.03%	1	3931
CodeGPT	1	0.04%	1	2643
StarCoder2-3b	3	0.21%	7	3306
CodeLlama-7b	3	0.43%	9	2069
DeepSeek-Coder-6b	8	0.74%	12	1622

is insufficient for effective bug detection. Improving the bug detection capability of generated test cases remains a critical challenge for future work.

Summary: LLM-generated test cases exhibit limited bug detection effectiveness, with low precision and high rates of build errors among failing tests, highlighting the need for improved methodologies to enhance bug detection capabilities.

5.3 Discussion of Metrics Comparison

In addition to runtime-based metrics, we incorporate text-based metrics to assess LLMs' performance in the test generation task on the *Methods2Test_{filter}* dataset. Notably, we include a syntax error rate, a measure that provides valuable insights without requiring code execution.

Table 9. Comparison of LLMs across different metrics on Defects4J and *Methods2Test_{filter}* benchmarks.

LLMs	Defects4J					<i>Methods2Test_{filter}</i>			
	Correct	Passing	Failing	Build Error	Syntax Error	EM	BLEU	CodeBLEU	Syntax Error
CodeBERT	5.56%	8.41%	5.99%	78.90%	6.70%	0.21%	11.96%	18.23%	9.57%
GraphCodeBERT	11.77%	14.02%	11.19%	65.89%	8.89%	0.55%	12.65%	18.51%	10.99%
UniXcoder	6.42%	8.12%	10.48%	69.02%	12.37%	0.46%	12.41%	18.82%	10.23%
CodeT5-base	15.91%	18.76%	14.90%	61.36%	4.98%	0.29%	6.11%	23.89%	10.09%
CodeT5p-220m	17.75%	19.79%	27.07%	50.26%	2.88%	0.30%	12.11%	23.00%	3.73%
PLBART-large	17.50%	20.25%	20.63%	52.96%	6.16%	0.05%	9.43%	22.16%	6.47%
CodeGPT	7.66%	9.64%	9.81%	39.67%	40.88%	0.09%	8.28%	21.50%	15.47%
StarCoder2-7b	20.78%	23.10%	23.16%	41.45%	12.30%	0.27%	5.56%	22.34%	5.92%
CodeLlama-7b	29.50%	32.14%	7.86%	30.87%	29.13%	0.37%	9.26%	25.11%	4.96%
DeepSeek-Coder-6b	33.68%	36.02%	9.00%	21.36%	33.62%	0.43%	8.61%	24.96%	5.18%

As presented in Table 9, all LLMs perform significantly worse on text-based metrics, with EM scores ranging from only 0.04% to 0.55%, a stark contrast to their performance on runtime-based metrics. In terms of BLEU and CodeBLEU scores, LLMs still underperform, with a BLEU score range from 5.56% to 12.65% and a CodeBLEU score range from 18.23% to 25.11%, remaining unexpectedly low compared to their performance on the other two tasks. Despite the low EM scores, the generated code maintains a relatively low syntax error rate, ranging from 4.96% to 15.47%, similar to results observed on Defects4J. Interestingly, decoder-only models also perform well in syntax error rate, likely due to the *Methods2Test* dataset's filtering process, which removes overly long inputs.

We attribute this lack of correlation to the diversity of the test cases. As mentioned in Section 3.4, half of the focal methods in the *Methods2Test* dataset include at least two related

test cases, reflecting real-world development practices. For example, the focal method ‘public Collection<Attribute> encode();’ in the Methods2Test dataset has eight associated test cases, each testing the method across different specific encoding types and verifying that the correct collection is returned. Although we remove duplicate test cases, the overall distribution remains unchanged. This may explain why LLMs perform poorly on text-based metrics yet relatively well on runtime-based metrics: the generated test cases may test the focal method from perspectives different from those in the ground truth. These findings indicate that, given the diversity of test cases and the real-world development context, runtime-based metrics are more suitable than text-based metrics for evaluating the effectiveness of automated test generation approaches.

Summary: LLMs may perform poorly on text-based metrics due to the diversity of test cases. Considering realistic development scenarios, it is recommended to use runtime-based metrics to evaluate the effectiveness of the automated test generation approaches.

6 Guidelines

We summarize some guidelines to suggest better practices for leveraging LLMs in unit testing.

(1) Potential of LLM-based approaches. As discussed in Section 4.1, our study shows that fine-tuning LLMs significantly outperforms state-of-the-art methods such as *ATLAS* for assertion generation, *ATHENATEST* for test generation, and *CEPROT* for test evolution across nearly all metrics. This improvement highlights the potential of LLMs for a wide range of unit testing tasks. Therefore, LLM-based approaches should be regarded as a primary strategy for achieving superior results.

(2) Incorporating Additional Post-Processing. As detailed in Section 4.1.1, LLMs fall short compared to A3Test, which, though also based on fine-tuning, incorporates a post-processing step to ensure naming consistency, parentheses completion, and test signature accuracy. This suggests that even a straightforward post-processing step can effectively enhance LLMs’ performance. Thus, exploring post-processing techniques, especially those that integrate program analysis knowledge, may be essential to enhance LLM effectiveness further.

(3) Importance of Input Length. In Section 4.1.3, we describe reallocating input space in the *CEPROT* approach by removing the edit sequence to include additional content—such as the original method, updated method, and original test. This adjustment led to a 4.7% improvement in EM and a 24.1% increase in CodeBLEU, demonstrating that extending input context length significantly enhances LLMs’ performance in the future.

(4) Selection of LLMs. As discussed in Section 4.2, we provide empirical recommendations for selecting LLMs in unit testing tasks. First, large-scale LLMs consistently outperform smaller ones, indicating that larger models should be prioritized when sufficient computing resources are available. The CodeLlama and DeepSeek-Coder series are especially worth considering for their strong performance. Second, encoder-decoder architectures perform better among models with fewer than one billion parameters. Thus, in resource-constrained settings, encoder-decoder models, particularly the CodeT5p series, maybe the optimal choice for unit testing tasks.

(5) Potential Issue with Failing Tests and Build Errors. As illustrated in Fig. 2, a considerable proportion of generated test cases fail when executed against production code, regardless of model size. Moreover, according to Table 2, even the top-performing model, DeepSeek-Coder-6b, still suffers from a high failure and build error rate of 30.36% on Defects4J. These failures, often resulting from incorrect test prefixes or assertions, significantly hinder the effectiveness of automated test case generation and impair the precision of bug detection. Therefore, reducing failing and build error test rates is crucial for further advancements.

(6) Runtime-based Metrics rather than Text-based Metrics. As discussed in Section 5.3, LLMs may perform poorly on text-based metrics due to the diversity of test cases, which significantly

impacts test generation tasks. The other two tasks may also be affected. Therefore, it is recommended to use runtime-based metrics to evaluate approaches for unit testing tasks.

7 Threats to Validity

Task Selection. Task selection is a critical factor affecting validity, as unit testing encompasses a wide domain with numerous tasks from diverse perspectives. To mitigate this threat, we select three widely recognized unit testing tasks representing different granularities and scenarios.

Data Leakage. Data leakage poses another potential risk, particularly in the test generation task using Defects4J dataset as an evaluation benchmark. To address this issue, we evaluate the performance of LLMs on the internal dataset to validate the robustness of our conclusions.

LLM Selection. The final threat to validity is the choice of LLMs. A limited number or scale of models could impact the robustness of our conclusions. To mitigate this, we select 37 LLMs with diverse architectures and a wide range of sizes, enabling the largest study in the literature.

8 Conclusion

In this paper, we conduct a large-scale empirical study on fine-tuning LLMs for unit testing, involving 37 widely used LLMs and three unit testing tasks. Our results demonstrate that LLMs outperform state-of-the-art approaches across nearly all metrics, highlighting the substantial advancement of LLMs in unit testing tasks. Besides, we analyze the impact of various factors on the performance of LLMs, such as model architectures, and discuss some key topics, such as data leakage and bug detection. Lastly, our findings provide various practical guidelines for future LLM-based unit testing research. Overall, this work highlights the potential of LLMs to advance unit testing and provides valuable insights for researchers to design effective unit testing approaches in the future.

9 Data Availability

Our experimental materials are available at https://github.com/iSEngLab/LLM4UT_Empirical.

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References

- [1] 2024. Commons CLI. <https://commons.apache.org/proper/commons-lang/>
- [2] 2024. Commons CSV. <https://commons.apache.org/proper/commons-csv/>
- [3] 2024. Commons Lang. <https://commons.apache.org/proper/commons-lang/>
- [4] 2024. google gson. <https://github.com/google/gson>
- [5] 2024. JFreeChart. <https://jfree.org/jfreechart/>
- [6] Toufique Ahmed, Kunal Suresh Pai, Premkumar T. Devanbu, and Earl T. Barr. 2024. Automatic Semantic Augmentation of Language Model Prompts (for Code Summarization). In *Proceedings of the 46th IEEE/ACM International Conference on Software Engineering, ICSE 2024, Lisbon, Portugal, April 14–20, 2024*. ACM, 220:1–220:13.
- [7] Saranya Alagarsamy, Chakkrit Tantithamthavorn, and Aldeida Aleti. 2024. A3Test: Assertion-Augmented Automated Test Case Generation. *Inf. Softw. Technol.* 176 (2024), 107565.
- [8] Luciano Baresi and Matteo Miraz. 2010. TestFul: Automatic Unit-Test Generation for Java Classes. In *Proceedings of the 32nd ACM/IEEE International Conference on Software Engineering - Volume 2, ICSE 2010, Cape Town, South Africa, 1–8 May 2010*. ACM, 281–284.
- [9] Cristian Cadar, Patrice Godefroid, Sarfraz Khurshid, Corina S. Pasareanu, Koushik Sen, Nikolai Tillmann, and Willem Visser. 2011. Symbolic Execution for Software Testing in Practice: Preliminary Assessment. In *Proceedings of the*

- 33rd International Conference on Software Engineering, ICSE 2011, Waikiki, Honolulu , HI, USA, May 21-28, 2011.* ACM, 1066–1071.
- [10] Yinghao Chen, Zehao Hu, Chen Zhi, Junxiao Han, Shuguang Deng, and Jianwei Yin. 2024. ChatUniTest: A Framework for LLM-Based Test Generation. In *Companion Proceedings of the 32nd ACM International Conference on the Foundations of Software Engineering, FSE 2024, Porto de Galinhas, Brazil, July 15-19, 2024*. ACM, 572–576.
 - [11] Vitaly Chipounov, Volodymyr Kuznetsov, and George Canea. 2011. S2E: a Platform for In-Vivo Multi-Path Analysis of Software Systems. In *Proceedings of the 16th International Conference on Architectural Support for Programming Languages and Operating Systems, ASPLOS 2011, Newport Beach, CA, USA, March 5-11, 2011*. ACM, 265–278.
 - [12] Ermira Daka and Gordon Fraser. 2014. A Survey on Unit Testing Practices and Problems. In *25th IEEE International Symposium on Software Reliability Engineering, ISSRE 2014, Naples, Italy, November 3-6, 2014*. IEEE Computer Society, 201–211.
 - [13] Siddhartha R. Dalal, Ashish Jain, Nachimuthu Karunanithi, J. M. Leaton, Christopher M. Lott, Gardner C. Patton, and Bruce M. Horowitz. 1999. Model-Based Testing in Practice. In *Proceedings of the 1999 International Conference on Software Engineering, ICSE' 99, Los Angeles, CA, USA, May 16-22, 1999*. ACM, 285–294.
 - [14] Elizabeth Dinella, Gabriel Ryan, Todd Mytkowicz, and Shuvendu K. Lahiri. 2022. TOGA: A Neural Method for Test Oracle Generation. In *44th IEEE/ACM 44th International Conference on Software Engineering, ICSE 2022, Pittsburgh, PA, USA, May 25-27, 2022*. ACM, 2130–2141.
 - [15] Eduard Paul Enoiu, Adnan Causevic, Thomas J. Ostrand, Elaine J. Weyuker, Daniel Sundmark, and Paul Pettersson. 2016. Automated Test Generation Using Model Checking: An Industrial Evaluation. *Int. J. Softw. Tools Technol. Transf.* 18, 3 (2016), 335–353.
 - [16] Zhangyin Feng, Daya Guo, Duyu Tang, Nan Duan, Xiaocheng Feng, Ming Gong, Linjun Shou, Bing Qin, Ting Liu, Daxin Jiang, and Ming Zhou. 2020. CodeBERT: A Pre-Trained Model for Programming and Natural Languages. In *Findings of the Association for Computational Linguistics: EMNLP 2020, Online Event, 16-20 November 2020 (Findings of ACL, Vol. EMNLP 2020)*. Association for Computational Linguistics, 1536–1547.
 - [17] Gordon Fraser and Andrea Arcuri. 2011. Evosuite: Automatic Test Suite Generation for Object-Oriented Software. In *SIGSOFT/FSE'11 19th ACM SIGSOFT Symposium on the Foundations of Software Engineering (FSE-19) and ESEC'11: 13th European Software Engineering Conference (ESEC-13), Szeged, Hungary, September 5-9, 2011*. ACM, 416–419.
 - [18] Angelo Gargantini and Constance L. Heitmeyer. 1999. Using Model Checking to Generate Tests from Requirements Specifications. In *Software Engineering - ESEC/FSE'99, 7th European Software Engineering Conference, Held Jointly with the 7th ACM SIGSOFT Symposium on the Foundations of Software Engineering, Toulouse, France, September 1999, Proceedings (Lecture Notes in Computer Science, Vol. 1687)*. Springer, 146–162.
 - [19] Siqi Gu, Chunrong Fang, Quanjun Zhang, Fangyuan Tian, Jianyi Zhou, and Zhenyu Chen. 2024. TestART: Improving LLM-based Unit Test via Co-evolution of Automated Generation and Repair Iteration. *CoRR* abs/2408.03095 (2024), arXiv-2408.
 - [20] Daya Guo, Qihao Zhu, Dejian Yang, Zhenda Xie, Kai Dong, Wentao Zhang, Guanting Chen, Xiao Bi, Y. Wu, Y. K. Li, Fulu Luo, Yingfei Xiong, and Wenfeng Liang. 2024. DeepSeek-Coder: When the Large Language Model Meets Programming - The Rise of Code Intelligence. *CoRR* abs/2401.14196 (2024), arXiv-2401.
 - [21] Yibo He, Jiaming Huang, Hao Yu, and Tao Xie. 2024. An Empirical Study on Focal Methods in Deep-Learning-Based Approaches for Assertion Generation. *Proc. ACM Softw. Eng.* 1, FSE (2024), 1750–1771.
 - [22] Soneya Binta Hossain and Matthew B. Dwyer. 2024. TOGLL: Correct and Strong Test Oracle Generation with LLMs. *CoRR* abs/2405.03786 (2024), arXiv-2405.
 - [23] Soneya Binta Hossain, Antonio Filieri, Matthew B. Dwyer, Sebastian G. Elbaum, and Willem Visser. 2023. Neural-Based Test Oracle Generation: A Large-Scale Evaluation and Lessons Learned. In *Proceedings of the 31st ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering, ESEC/FSE 2023, San Francisco, CA, USA, December 3-9, 2023*. ACM, 120–132.
 - [24] Xinyi Hou, Yanjie Zhao, Yue Liu, Zhou Yang, Kailong Wang, Li Li, Xiapu Luo, David Lo, John C. Grundy, and Haoyu Wang. 2023. Large Language Models for Software Engineering: A Systematic Literature Review. *CoRR* abs/2308.10620 (2023), arXiv-2308.
 - [25] Xing Hu, Zhuang Liu, Xin Xia, Zhongxin Liu, Tongtong Xu, and Xiaohu Yang. 2023. Identify and Update Test Cases When Production Code Changes: A Transformer-Based Approach. In *38th IEEE/ACM International Conference on Automated Software Engineering, ASE 2023, Luxembourg, September 11-15, 2023*. IEEE, 1111–1122.
 - [26] Raymond Li, Loubna Ben Allal, Yangtian Zi, Niklas Muennighoff, Denis Kocetkov, Chenghao Mou, Marc Marone, Christopher Akiki, Jia Li, Jenny Chim, et al. 2023. StarCoder: May the Source Be with You! *Trans. Mach. Learn. Res.* 2023 (2023).
 - [27] Jun Liu, Jiwei Yan, Yuanyuan Xie, Jun Yan, and Jian Zhang. 2024. Augmenting LLMs to Repair Obsolete Test Cases with Static Collector and Neural Reranker. *CoRR* abs/2407.03625 (2024), arXiv-2407.

- [28] Zhongxin Liu, Kui Liu, Xin Xia, and Xiaohu Yang. 2023. Towards More Realistic Evaluation for Neural Test Oracle Generation. In *Proceedings of the 32nd ACM SIGSOFT International Symposium on Software Testing and Analysis, ISSTA 2023, Seattle, WA, USA, July 17-21, 2023*. ACM, 589–600.
- [29] Lei Ma, Cyrille Artho, Cheng Zhang, Hiroyuki Sato, Johannes Gmeiner, and Rudolf Ramler. 2015. GRT: Program-Analysis-Guided Random Testing (T). In *30th IEEE/ACM International Conference on Automated Software Engineering, ASE 2015, Lincoln, NE, USA, November 9-13, 2015*. IEEE Computer Society, 212–223.
- [30] Chao Ni, Xiaoya Wang, Liushan Chen, Dehai Zhao, Zhengong Cai, Shaohua Wang, and Xiaohu Yang. 2024. CasModaTest: A Cascaded and Model-Agnostic Self-Directed Framework for Unit Test Generation. *CoRR* abs/2406.15743 (2024), arXiv-2406.
- [31] Erik Nijkamp, Bo Pang, Hiroaki Hayashi, Lifu Tu, Huan Wang, Yingbo Zhou, Silvio Savarese, and Caiming Xiong. 2023. CodeGen: An Open Large Language Model for Code with Multi-Turn Program Synthesis. In *The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023*. OpenReview.net.
- [32] A. Jefferson Offutt and Aynur Abdurazik. 1999. Generating Tests from UML Specifications. In *«UML»'99: The Unified Modeling Language - Beyond the Standard, Second International Conference, Fort Collins, CO, USA, October 28-30, 1999, Proceedings (Lecture Notes in Computer Science, Vol. 1723)*. Springer, 416–429.
- [33] Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll L. Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul F. Christiano, Jan Leike, and Ryan Lowe. 2022. Training Language Models to Follow Instructions with Human Feedback. In *Advances in Neural Information Processing Systems 35: Annual Conference on Neural Information Processing Systems 2022, NeurIPS 2022, New Orleans, LA, USA, November 28 - December 9, 2022, Vol. 35*. 27730–27744.
- [34] Carlos Pacheco and Michael D. Ernst. 2007. Randoop: Feedback-Directed Random Testing for Java. In *Companion to the 22nd Annual ACM SIGPLAN Conference on Object-Oriented Programming, Systems, Languages, and Applications, OOPSLA 2007, October 21-25, 2007, Montreal, Quebec, Canada*. ACM, 815–816.
- [35] Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. BLEU: a Method for Automatic Evaluation of Machine Translation. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, July 6-12, 2002, Philadelphia, PA, USA*. ACL, 311–318.
- [36] Corina S. Pasareanu, Peter C. Mehlitz, David H. Bushnell, Karen Gundy-Burlet, Michael R. Lowry, Suzette Person, and Mark Pape. 2008. Combining Unit-Level Symbolic Execution and System-Level Concrete Execution for Testing NASA Software. In *Proceedings of the ACM/SIGSOFT International Symposium on Software Testing and Analysis, ISSTA 2008, Seattle, WA, USA, July 20-24, 2008*. ACM, 15–26.
- [37] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer. *J. Mach. Learn. Res.* 21 (2020), 140:1–140:67.
- [38] Shuo Ren, Daya Guo, Shuai Lu, Long Zhou, Shujie Liu, Duyu Tang, Neel Sundaresan, Ming Zhou, Ambrosio Blanco, and Shuai Ma. 2020. CodeBLEU: a Method for Automatic Evaluation of Code Synthesis. *CoRR* abs/2009.10297 (2020), arXiv-2009.
- [39] Baptiste Rozière, Jonas Gehring, Fabian Gloeckle, Sten Sootla, Itai Gat, Xiaoqing Ellen Tan, Yossi Adi, Jingyu Liu, Tal Remez, Jérémie Rapin, Artyom Kozhevnikov, Ivan Evtimov, Joanna Bitton, Manish Bhatt, Cristian Canton-Ferrer, Aaron Grattafiori, Wenhan Xiong, Alexandre Défossez, Jade Copet, Faisal Azhar, Hugo Touvron, Louis Martin, Nicolas Usunier, Thomas Scialom, and Gabriel Synnaeve. 2023. Code Llama: Open Foundation Models for Code. *CoRR* abs/2308.12950 (2023), arXiv-2308.
- [40] Max Schäfer, Sarah Nadi, Aryaz Eghbali, and Frank Tip. 2024. An Empirical Evaluation of Using Large Language Models for Automated Unit Test Generation. *IEEE Trans. Software Eng.* 50, 1 (2024), 85–105.
- [41] Weisong Sun, Chunrong Fang, Yudu You, Yuchen Chen, Yi Liu, Chong Wang, Jian Zhang, Quanjun Zhang, Hanwei Qian, Wei Zhao, Yang Liu, and Zhenyu Chen. 2023. A Prompt Learning Framework for Source Code Summarization. *CoRR* abs/2312.16066 (2023), arXiv-2312.
- [42] Weifeng Sun, Meng Yan, Zhongxin Liu, Xin Xia, Yan Lei, and David Lo. 2023. Revisiting the Identification of the Co-evolution of Production and Test Code. *ACM Trans. Softw. Eng. Methodol.* 32, 6 (2023), 152:1–152:37.
- [43] Michele Tufano, Shao Kun Deng, Neel Sundaresan, and Alexey Svyatkovskiy. 2022. METHODS2TEST: A Dataset of Focal Methods Mapped to Test Cases. In *19th IEEE/ACM International Conference on Mining Software Repositories, MSR 2022, Pittsburgh, PA, USA, May 23-24, 2022*. ACM, 299–303.
- [44] Michele Tufano, Dawn Drain, Alexey Svyatkovskiy, Shao Kun Deng, and Neel Sundaresan. 2020. Unit Test Case Generation with Transformers and Focal Context. *arXiv e-prints* abs/2009.05617 (2020), arXiv-2009.
- [45] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is All you Need. In *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA*. 5998–6008.

- [46] Junjie Wang, Yuchao Huang, Chunyang Chen, Zhe Liu, Song Wang, and Qing Wang. 2024. Software Testing With Large Language Models: Survey, Landscape, and Vision. *IEEE Trans. Software Eng.* 50, 4 (2024), 911–936.
- [47] Yue Wang, Hung Le, Akhilesh Gotmare, Nghi D. Q. Bui, Junnan Li, and Steven C. H. Hoi. 2023. CodeT5+: Open Code Large Language Models for Code Understanding and Generation. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing, EMNLP 2023, Singapore, December 6-10, 2023*. Association for Computational Linguistics, 1069–1088.
- [48] Yue Wang, Weishi Wang, Shafiq R. Joty, and Steven C. H. Hoi. 2021. CodeT5: Identifier-aware Unified Pre-trained Encoder-Decoder Models for Code Understanding and Generation. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, EMNLP 2021, Virtual Event / Punta Cana, Dominican Republic, 7-11 November, 2021*. Association for Computational Linguistics, 8696–8708.
- [49] Cody Watson, Michele Tufano, Kevin Moran, Gabriele Bavota, and Denys Poshyvanyk. 2020. On Learning Meaningful Assert Statements for Unit Test Cases. In *ICSE '20: 42nd International Conference on Software Engineering, Seoul, South Korea, 27 June - 19 July, 2020*. ACM, 1398–1409.
- [50] Yuxiang Wei, Zhe Wang, Jiawei Liu, Yifeng Ding, and Lingming Zhang. 2024. Magicoder: Empowering Code Generation with OSS-Instruct. In *Forty-first International Conference on Machine Learning, ICML 2024, Vienna, Austria, July 21-27, 2024*. OpenReview.net.
- [51] Tao Xie, Darko Marinov, Wolfram Schulte, and David Notkin. 2005. Symstra: A Framework for Generating Object-Oriented Unit Tests Using Symbolic Execution. In *Tools and Algorithms for the Construction and Analysis of Systems, 11th International Conference, TACAS 2005, Held as Part of the Joint European Conferences on Theory and Practice of Software, ETAPS 2005, April 4-8, 2005, Proceedings (Lecture Notes in Computer Science, Vol. 3440)*. Springer, 365–381.
- [52] Lin Yang, Chen Yang, Shutao Gao, Weijing Wang, Bo Wang, Qihao Zhu, Xiao Chu, Jianyi Zhou, Guangtai Liang, Qianxiang Wang, and Junjie Chen. 2024. An Empirical Study of Unit Test Generation with Large Language Models. *CoRR* abs/2406.18181 (2024), arXiv–2406.
- [53] Ahmadreza Saboor Yaraghi, Darren Holden, Nafiseh Kahani, and Lionel C. Briand. 2024. Automated Test Case Repair Using Language Models. *CoRR* abs/2401.06765 (2024), arXiv–2401.
- [54] Hao Yu, Yiling Lou, Ke Sun, Dezhong Ran, Tao Xie, Dan Hao, Ying Li, Ge Li, and Qianxiang Wang. 2022. Automated Assertion Generation via Information Retrieval and Its Integration with Deep learning. In *44th IEEE/ACM 44th International Conference on Software Engineering, ICSE 2022, Pittsburgh, PA, USA, May 25-27, 2022*. ACM, 163–174.
- [55] Wei Yuan, Quanjun Zhang, Tieke He, Chunrong Fang, Nguyen Quoc Viet Hung, Xiaodong Hao, and Hongzhi Yin. 2022. CIRCLE: Continual Repair across Programming Languages. In *ISSTA '22: 31st ACM SIGSOFT International Symposium on Software Testing and Analysis, Virtual Event, South Korea, July 18 - 22, 2022*. ACM, 678–690.
- [56] Zhiqiang Yuan, Mingwei Liu, Shiji Ding, Kaixin Wang, Yixuan Chen, Xin Peng, and Yiling Lou. 2024. Evaluating and Improving ChatGPT for Unit Test Generation. *Proc. ACM Softw. Eng.* 1, FSE (2024), 1703–1726.
- [57] Quanjun Zhang, Chunrong Fang, Yuxiang Ma, Weisong Sun, and Zhenyu Chen. 2024. A Survey of Learning-based Automated Program Repair. *ACM Trans. Softw. Eng. Methodol.* 33, 2 (2024), 55:1–55:69.
- [58] Quanjun Zhang, Chunrong Fang, Weisong Sun, Shengcheng Yu, Yutao Xu, and Yulei Liu. 2022. Test Case Prioritization Using Partial Attention. *J. Syst. Softw.* 192 (2022), 111419.
- [59] Quanjun Zhang, Chunrong Fang, Yang Xie, Yuxiang Ma, Weisong Sun, Yun Yang, and Zhenyu Chen. 2024. A Systematic Literature Review on Large Language Models for Automated Program Repair. *CoRR* abs/2405.01466 (2024), arXiv–2405.
- [60] Quanjun Zhang, Chunrong Fang, Yang Xie, Yaxin Zhang, Yun Yang, Weisong Sun, Shengcheng Yu, and Zhenyu Chen. 2023. A Survey on Large Language Models for Software Engineering. *CoRR* abs/2312.15223 (2023), arXiv–2312.
- [61] Quanjun Zhang, Chunrong Fang, Bowen Yu, Weisong Sun, Tongke Zhang, and Zhenyu Chen. 2024. Pre-Trained Model-Based Automated Software Vulnerability Repair: How Far are We? *IEEE Trans. Dependable Secur. Comput.* 21, 4 (2024), 2507–2525.
- [62] Quanjun Zhang, Chunrong Fang, Tongke Zhang, Bowen Yu, Weisong Sun, and Zhenyu Chen. 2023. Gamma: Revisiting Template-Based Automated Program Repair Via Mask Prediction. In *38th IEEE/ACM International Conference on Automated Software Engineering, ASE 2023, Luxembourg, September 11-15, 2023*. IEEE, 535–547.
- [63] Quanjun Zhang, Ye Shang, Chunrong Fang, Siqi Gu, Jianyi Zhou, and Zhenyu Chen. 2024. TestBench: Evaluating Class-Level Test Case Generation Capability of Large Language Models. *arXiv e-prints* abs/2409.17561 (2024), arXiv–2409.
- [64] Quanjun Zhang, Weifeng Sun, Chunrong Fang, Bowen Yu, Hongyan Li, Meng Yan, Jianyi Zhou, and Zhenyu Chen. 2024. Exploring Automated Assertion Generation via Large Language Models. *ACM Trans. Softw. Eng. Methodol.* (Oct. 2024). <https://doi.org/10.1145/3699598> Just Accepted.
- [65] Quanjun Zhang, Tongke Zhang, Juan Zhai, Chunrong Fang, Bowen Yu, Weisong Sun, and Zhenyu Chen. 2023. A Critical Review of Large Language Model on Software Engineering: An Example from ChatGPT and Automated Program Repair. *CoRR* abs/2310.08879 (2023), arXiv–2310.
- [66] Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, et al. 2023. A Survey of Large Language Models. *arXiv e-prints* abs/2303.18223 (2023), arXiv–2303.