Advancing Bug Detection in Fastjson2 with Large Language Models Driven Unit Test Generation

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Abstract—Data-serialization libraries are essential tools in software development, responsible for converting between programmable data structures and data persistence formats. Among them, JSON is the most popular choice for exchanging data between different systems and programming languages, while JSON libraries serve as the programming toolkit for this task. Despite their widespread use, bugs in JSON libraries can cause severe issues such as data inconsistencies and security vulnerabilities. Unit test generation techniques are widely adopted to identify bugs in various libraries. However, there is limited systematic testing effort specifically for exposing bugs within JSON libraries in industrial practice. In this paper, we propose JSONTESTGEN, an approach leveraging large language models (LLMs) to generate unit tests for fastjson2, a popular opensource JSON library from Alibaba. Pre-trained on billions of open-source text and code corpora, LLMs have demonstrated remarkable abilities in programming tasks. Based on historical bug-triggering unit tests, we utilize LLMs to generate more diverse test cases by incorporating JSON domain-specific mutation rules. To systematically and efficiently identify potential bugs, we adopt differential testing on the results of the generated unit tests. Our evaluation shows that JSONTESTGEN outperforms existing test generation tools in unknown defect detection. With JSONTESTGEN, we found 34 real bugs in fastjson2, 30 of which have already been fixed, including 12 non-crashing bugs. While manual inspection reveals that LLM-generated tests can be erroneous, particularly with self-contradictory assertions, we demonstrate that LLMs have the potential for classifying falsepositive test failures. This suggests a promising direction for improved test oracle automation in the future.

I. INTRODUCTION

Data-serialization libraries are crucial tools in modern software development. They are responsible for converting between programmable data structures and data persistence formats, enabling efficient data exchange, storage, and retrieval. Well-known data-serialization libraries include Gson [1] for JSON format, JAXB [2] for XML format, and Protocol Buffers [3] for a specialized binary format. Among these formats, JSON (JavaScript Object Notation) [4] is pervasively used in various application scenarios like web APIs, scientific

computing, and data management [5]. JSON libraries provide functionalities such as parsing JSON data into language-specific objects, serializing objects into JSON format, and manipulating JSON data structures. Despite their prevalence, JSON libraries can have bugs [6] that lead to serious consequences, affecting the software applications that depend on them. Therefore, it is crucial to ensure the quality of JSON libraries.

Fuzzing [7] is a powerful testing technique to find bugs via diverse input generation. Various attempts have been made to fuzz JSON-related artifacts [8]-[10]. For instance, the JSON fuzzer for fastjson2 [11] in OSS-Fuzz [8] targets at a single predefined parsing method JSON.parse(String).generating input to trigger crashes. EvoGFuzz [10] generates input for eight JSON parsers and exposes their defects. Recently, Hopper [9] is proposed to fuzz general libraries with effective API calls. While both have been shown effective in finding bugs in JSON libraries, they still have limitations. They only fuzz a limited number of predefined parsing methods and fall short in detecting non-crashing functional bugs, which can produce unexpected outputs without causing program crashes. These issues, often arising from program logic errors, are also prevalent in other artifacts like Android apps [12]. The lack of test oracles further complicates their detection [13].

Unit testing is a software testing technique where developers test individual functions or methods to ensure correct implementation [14]. For example, JUnitTestGen [14] generates unit test cases by mining Android API usage to detect various compatibility issues. Almasi et al. [15] examine the effectiveness of test generation tools in identifying real faults within a financial application. These existing works cannot be directly applied to generate tests tailored for JSON libraries.

Recent advancements in large language models (LLMs) [16] have significantly impacted many software engineering tasks [17], [18]. Researchers have utilized LLMs to test deep learning libraries [19], [20], to fuzz JavaScript engines [21], and to fuzz network protocols [22]. Additionally, studies have evaluated the effectiveness of LLMs in automated unit test

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generation [23]–[26] and improving the quality of unit tests generated by LLMs [27]–[29]. Yet, few work has utilized LLMs on dedicated libraries such as data-serialization libraries, leaving their potential in this area unexplored.

In this work, we leverage LLMs to test *fastjson2* [11], an open-source JSON library from Alibaba, which has been widely used in industrial practice. With more than 3.7k stars and 12.6k dependent projects on GitHub, *fastjson2* is the fourth most popular JSON library on Maven. To address the previous limitations, we propose a highly automated LLM-based approach, JSONTESTGEN, which utilizes existing bug-triggering unit tests to generate more diverse tests covering various library APIs. We adopt differential testing, comparing the results from *fastjson* and *fastjson2* to identify both crashinducing and non-crashing logic bugs that are previously unknown. To enhance the diversity of the generated tests, we introduce a mutation paradigm focusing on the key features of JSON libraries. To sum up, this work makes the following main contributions from a practical perspective:

- To the best of our knowledge, we are the first to propose an LLM-based approach for identifying bugs in a widelyused JSON library. JSONTESTGEN learns from existing unit tests to automatically generate diverse new tests for bug detection.
- We design effective prompting strategies that incorporate JSON-specific mutation rules, guiding LLMs to produce high-quality unit tests, which can be applied to future JSON library testing.
- We have successfully uncovered 34 previously unknown bugs in *fastjson2*, including 12 non-crashing bugs that are challenging for existing tools to detect.
- We analyze the failed cases and investigate the potential of LLMs to identify false positive test failures caused by incorrect testing logic, exploring a promising direction for improved test oracle automation.

II. BACKGROUND

A. Large Language Models

Large Language Models (LLMs) [30] have transformed natural language processing (NLP), excelling in tasks like text classification [31] and summarization [32]. In addition to traditional NLP tasks, recent developments have highlighted the effectiveness of LLMs in code-related applications [33], such as program synthesis [34] and repair [18]. LLMs are built upon the Transformer architecture [35], which utilizes self-attention mechanisms to process and understand complex long-term information. These models are typically pre-trained on extensive text corpora using self-supervised learning, enabling them to capture a broad range of knowledge with billions of parameters [30]. Beyond pre-training, LLMs are further refined through instruction-tuning [36] and reinforcement learning from human feedback (RLHF) [37], which enhances their ability to follow complex instructions and produce humanaligned outputs.

Prompt engineering is crucial for deploying LLMs in real-world applications. It involves designing prompts that effectively guide the model's behavior and fully leverage the incontext learning ability of LLMs [30]. This approach utilizes carefully crafted prompts, including relevant examples [38] and step-by-step instructions [39], to enhance their performance on specific tasks.

B. Unit Test Generation

Unit test generation techniques aim to automatically create tests for a focal method, consisting of a test prefix and a test oracle [13]. The test prefix sets up the conditions necessary to execute the focal method, while the test oracle, typically in the form of assertions, verifies that the method behaves as expected [23]. Traditional approaches to this problem include search-based [40], random-based [41], and model checking methods [42]. A notable example is Evosuite [40], which applies evolutionary algorithms to generate test cases aimed at maximizing code coverage. While achieving reasonable coverage, these techniques often produce tests that lack readability and maintainability compared to manually written ones, making them challenging for developers to directly use in practice [15], [23], [26].

More recent research has explored the use of deep learning techniques to improve unit test generation [43], [44]. Some methods treat test generation as a neural machine translation task, where models are trained to generate test prefixes and assertions based on the input method. The emergence of LLMs has further advanced this area, enabling test generation through prompt engineering [23]–[25]. While they have shown promise in generating high-quality tests, challenges remain in ensuring the reliability and correctness of the generated tests, as LLM outputs can be non-deterministic and prone to hallucinations [28].

III. JSONTENGEN

Figure 1 illustrates our technical approach of utilizing existing unit tests to discover new bugs in fastjson2. We first collect issue-relevant unit tests from fastjson2's GitHub repository. These unit tests serve as the original dataset, revealing historical bugs in fastjson2. They are then diversified to trigger bugs in various scenarios through two stages: Understanding and Generation. In the Understanding stage, key information such as subject APIs and core operations is extracted from the code by prompting an LLM for a summary. During the Generation stage, the LLM generates new unit tests by integrating the previous code, summary, and specific mutation guidance about JSON libraries. Finally, the newly generated unit tests are executed to test fastjson2. However, directly executing the unit tests and observing their results may not be feasible since code generated by LLMs can sometimes be problematic in semantics [45], [46]. To address this, we compare the test results in a differential manner [47] to identify potentially buggy test cases.

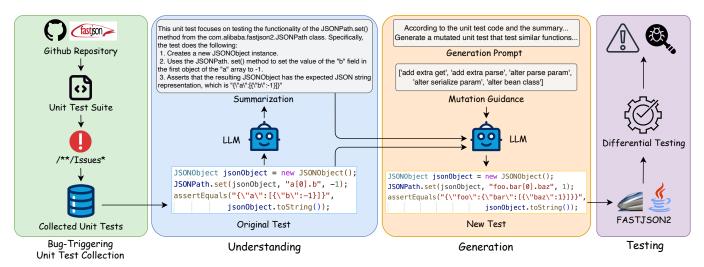


Fig. 1. Overview of JSONTESTGEN

A. Bug-Triggering Unit Test Collection

The study of testing with historical bugs has been a research focus for years. One recent study demonstrates that reusing code snippets with small modifications from historical bug reports can effectively identify bugs in C/C++ compilers [48]. Based on this idea, we first collect the unit tests in *fastjson2*'s repository [11]. This aligns with industrial practices, as *fastjson2* is actively maintained with over 1,200 issues on GitHub. Many of these issues have led to the inclusion of unit tests in its regression test suite to ensure robustness.

To extract tests related to historical issues, we use regular expression pattern matching to select files whose filenames contain the keyword "issue" (e.g., Issue100.java for the GitHub issue 100 [49]), following the developers' naming conventions. These tests serve as our original data D, which contains the necessary test classes that trigger bugs in the previous releases of fastjson2. Instead of collecting issues and pull requests (PRs) from GitHub issue-tracking systems, we gather code from unit tests because they are more concise, precise, and well-formatted. These unit tests are generally small but include necessary steps to trigger bugs in particular functionalities. Furthermore, since they are reviewed by developers, the assertions in these tests are correct and reliable.

B. Understanding

At the start of each running loop, JSONTESTGEN takes a test $t_{original}$ from original data D as the seed example. In the **Understanding** phase, an LLM is asked to summarize the code in $t_{original}$, such as explaining the targeted function under test and the operations taken. The prompt is $t_{original}$ +"Summarize what this unit test focuses on". Though generated by the LLM itself, the explanation will serve as in-context information to help the LLM better learn the intentions and behaviors of the code, as suggested by [50] and [51].

C. Mutation Strategies

By manually reviewing the APIs of fastjson2 alongside those of Gson [1] and Jackson [52], we summarize three

core functionalities of JSON libraries: data validation, manipulation, and serialization/deserialization. This focus prioritizes industrial practice and relevance, as these libraries implement the JSON specification [4], ensuring consistent capabilities. Specifically, they validate the syntax of JSON data, offer mechanisms to retrieve, update, or remove values within the JSON structure, and support the conversion of objects to JSON strings and vice versa.

Additionally, we have explored various manual mutations, including parsing data of different types, modifying bean classes for different internal structures, and serializing objects to strings with multiple configurations. Consequently, we craft five mutation rules as additional tips for LLMs, tailored to the features of a JSON library:

- 1. Extra data validation. Fastjson2 has two primary objects for representing JSON data: JSONObject and JSONArray. Both of them offer several getter methods for data retrieval, using a key (for JSONObject) and an index (for JSONArray). The instruction asks the model to add extra getter invocations and assert the returned value, to validate the data integrity and consistency.
- **2. Extra parsing.** Fastjson2 provides several APIs for parsing JSON data, such as parseObject and parseArray, which can process data from strings and byte streams. The instruction requires the LLM to add extra parsing methods to cover more scenarios.
- **3. Parsing configurations.** Over ten descrialization features are supported in *fastjson2*, such as TrimString and UseNativeObject. We provide an example usage of descrialization configuration and a list of candidate options, and ask the LLM to modify the parameters to test various parsing configurations.
- **4. Serialization configurations.** Similar to parsing, *fastj-son2* offers even more serialization configurations to allow flexible customization. The model is asked to alter the serialization settings from a collection of possible choices.
- **5. Modifying beans.** In the context of a JSON library, a "bean" refers to a Java object that follows standard conven-

tions. Beans are used to map JSON data to Java objects and vice versa during serialization and deserialization. The LLM is directed to modify the bean definitions by changing field names, data types, and adding or removing fields to test diverse scenarios.

The key difference between mutating test cases using direct syntax rules and generating them with LLMs is the ability to make nuanced modifications. While syntax rule matching is feasible, it is hard to adjust corresponding assertions in the meantime, which is crucial since minor changes can lead to differences in assertion outcomes. In contrast, LLMs are context-aware and can implicitly handle these adjustments, resulting in meaningful tests that accommodate such variations, as demonstrated in Listing 2.

D. Generation

During the **Generation** phase, JSONTESTGEN prompts the LLM to generate a new test t_{new} using the original test $t_{original}$, the summary s (with corresponding prompt p_s), and the mutation rule m (Section III-C). The system prompt sys is "You are a helpful assistant". The prompt for generation p_{gen} is "Include necessary import statements and return a complete test". JSONTESTGEN then combines all historical information into the context C to query the LLM, following the conversation format with roles System, User, and Assistant [53]. The illustration is shown in Equation 1 and Figure 2.

$$C = \langle sys \rangle + \langle t_{original} \rangle + \langle p_s \rangle + \langle s \rangle + \langle m \rangle + \langle p_{gen} \rangle,$$

$$t_{new} = LLM(C)$$
 (1)

System: You are a helpful assistant.

User: Here is a unit test:

<insert unit test here>
Please summarize what this unit test focuses on.

Assistant: <LLM generated summarization>
User: According to the unit test and the summary above, generate a new unit test that tests the same or similar functions. [Write a new test that cinsert mutation rule>.] Include necessary import statements and return a complete test case.

Assistant: Here is...<

LLM generated test>

Fig. 2. Context of test generation

E. Test Oracle

The empirical study by Siddiq et al. has demonstrated the low quality of LLM-generated unit tests [27]. Therefore, a failed unit test may not necessarily indicate a bug but rather reflects the logically incorrect code produced due to the LLM's limited capabilities. Thus, we cannot solely rely on the test results as golden test oracles.

To address this issue, JSONTESTGEN adopts differential testing in the **Testing** phase, and inconsistencies in the results indicate potential bugs. We assume that the three relevant implementations, *fastjson*, *fastjson-compatible*, and *fastjson2*, should produce identical results in their core functionalities. In case of intentionally inconsistent behaviors among the three implementations, we will manually review them and 3 discuss

with the developers of *fastjson2*. The backgrounds and details of these implementations are as follows:

Fastjson is a popular JSON library from Alibaba. It has been continuously maintained since 2011. However, it has faced severe security issues like remote code execution vulnerabilities [54] and is no longer actively maintained.

Fastjson2 is an upgrade version of *fastjson* that enhances performance and security. It retains most of the basic APIs from *fastjson* but updates some class and method names for better clarity. The goal is to provide a high-performance JSON library for the next decade at Alibaba.

Fastjson-compatible offers compatible API signatures with *fastjson* to accommodate its extensive user base. However, their underlying implementations come from *fastjson2*.

JSONTESTGEN compares the running results of the generated tests using these three packages, where any inconsistencies may indicate potential bugs. Since *fastjson* and *fastjson2* do not necessarily have identical APIs, we only consider those successfully compiled across all packages. It is also worth mentioning that our comparison focuses on the final test outcomes—whether they pass, fail, or throw exceptions—rather than analyzing intermediate outputs or program states. This setting helps detect possible non-crashing bugs, such as mixed pass/failure results without exceptions, while avoiding the need for complex instrumentation.

IV. EXPERIMENTAL SETUP

A. Research Questions

Our evaluation aims to answer the following research questions (RQs):

- RQ1: How does JSONTESTGEN perform compared with the state-of-the-art test generation tools?
- RQ2: How do different components contribute to JSON-TESTGEN?
- RQ3: What real-world bugs can JSONTESTGEN successfully identify?
- RQ4: What are the main causes of false-positive failures in LLM-generated unit tests for fastjson2, and how effectively can LLMs distinguish between genuine bugs and these failures?

B. Environments

Our experiments were conducted on a 64-core workstation running Ubuntu 20.04.6 LTS with two NVIDIA Quadro RTX 6000 GPUs, using the JDK version OpenJDK 1.8.0-382 and Apache Maven 3.6.3 with Junit5 5.11.0. The subject libraries include *fastjson2* 2.0.49, *fastjson-compatible* 2.0.49, and *fastjson* 1.2.83, all of which were the latest versions at the time of our experiment.

C. LLM Selection

We use 3 representative LLMs in our experiments, including closed-source commercial LLMs and open-source LLMs:

• **GPT-3.5 Turbo**: GPT-3.5 is a set of proprietary LLMs offered by OpenAI, and it is the default model used in the

early ChatGPT product [16]. We access GPT-3.5 Turbo [55] through OpenAI's API services [53].

- Llama3: Llama3 is a family of LLMs with state-of-theart performance, developed and open-sourced by Meta [56]. Due to hardware constraints, we use the instruction-tuned version with 8b parameters *Llama-3-8b-instruct* from Huggingface [57].
- **GPT-4o**: GPT-4o is a flagship commercial model released by OpenAI [58]. It is one of the most capable models for complex and multi-step tasks in the community [59].

In our main experiments (Sections V-B2 and V-B3), we utilize GPT-3.5 Turbo and Llama3 for test generation, while GPT-40 is employed for test classification in Section VI-B. We excluded GPT-40 from test generation because GPT-3.5 Turbo is faster and more cost-effective for producing large volumes of tests, costing ten times less than GPT-40 [60]. However, in Section VI-B, we aim to examine the performance of LLMs in classification tasks that involve complex reasoning. Given GPT-40's superior reasoning capabilities, we choose it as a representative. Additionally, the smaller number of samples makes the experiment affordable.

D. Baseline Methods

We include the following two baseline methods to compare with our JSONTESTGEN:

- Zest: Zest [61] is a coverage-guided fuzzing tool that utilizes code coverage and input validity feedback to guide a QuickCheck-style generator in producing structured inputs that can uncover deep semantic bugs. We use the JQF platform [62] to run fuzzing experiments with Zest.
- ChatUniTest: ChatUniTest is an automated unit test generation framework based on ChatGPT that showcases reliable coverage across diverse projects [25]. Similar tools include ChatTester [23] and TestSpark [63], which are also LLM-based test generators. We choose ChatUniTest as a representative due to its simplicity and ease of integration through its plug-and-play Maven plugin [64], which we use to generate unit tests for fastjson2. We use the default configuration options in [64] unless otherwise specified.

E. Evaluation Metrics

We use the widely adopted measurement of code coverage and the number of newly detected bugs. The coverage data is collected via JaCoCo [65] with both instruction- and branch-levels of granularity. All detected bugs will undergo manual verification to see if they are new and unique.

V. EXPERIMENTAL RESULTS

A. RQ1: Comparison with Baseline Methods

To run experiments with Zest, a test driver and input generator must be manually written. For easier implementation and evaluation, we use the AsciiStringGenerator to generate string inputs for the target functions parse, parseArray, parseObject, and isValid, following the provided example in JQF [66]. During fuzzing, we notice

TABLE I COMPARISON WITH ZEST

	Instruction Coverage (%)		Branch Coverage (%)		
Methods Zest		JSONTESTGEN	Zest	JSONTESTGEN	
parse	80.00	94.29	65.00	75.00	
parseObject	38.60	100.00	25.00	91.67	
parseArray	39.29	91.38	25.00	66.67	
isValid	51.72	89.66	25.00	50.00	

TABLE II COMPARISON WITH CHATUNITEST

	Instruction Co	verage (%)	Branch Coverage (%)		
Classes	ChatUniTest	JSON TESTGEN	ChatUniTest	JSON TESTGEN	
JSONObject	47.47	37.53	44.73	28.36	
JSONArray	52.51	26.35	50.28	16.76	
JSONPath	11.16	28.17	9.70	25.76	
JSON	6.50	36.14	5.23	26.23	

that the status panel occasionally freezes with no further updates after a few seconds¹. We report the results of the experiments that ran the longest, typically around six to ten seconds, as determined by manual review.

For ChatUniTest, we utilize GPT-3.5 Turbo as the base LLM, generating three tests per method and allowing a maximum of three repair process rounds. All other parameters are set to their default values from [64]. Since generating unit tests for the entire project consumes a significant number of tokens, we focus on generating tests for four commonly used classes due to limited budget: JSON, JSONObject, JSONArray, and JSONPath.

In JSONTESTGEN, we have collected a total of 681 bug-triggering unit tests. We also employ GPT-3.5 Turbo to generate three tests for each of the collected unit tests without adding mutation rules to the prompts (the rationale for this is discussed in Section V-B3). We then reported the coverage results for the selected classes.

Table I shows that JSONTESTGEN consistently surpasses Zest in both coverage criteria. Although Zest is structure-aware and effective at testing the semantic analysis phase of programs [61], its performance may rely on the quality of input generators. For instance, the AsciiStringGenerator [67] is one possible simple generator in Zest that generates strings by producing random ASCII characters within the range of 1 to 127. These generators must be manually crafted, which requires extra domain knowledge for non-trivial programs under test [68]. This dependency on hand-written generators can limit Zest's ability to adapt to diverse input scenarios and introduces an additional overhead that may not be feasible in all cases.

In contrast, JSONTESTGEN generates unit tests that cover multiple methods and their combinations within a library. It can also generate tests that correctly invoke complex methods with multiple configuration arguments, rather than targeting individual methods separately.

¹Similar to the issue reported in https://github.com/rohanpadhye/JQF/issues/

TABLE III
TESTS EXECUTION RESULTS
WITH/WITHOUT SUMMARIZATION (%)

	Summarization		
Execution Result	Yes	No	
Pass	56.3	54.2	
Failure / Exception	29.8	20.1	
Compile Error	$13.9 \ (11.8 \downarrow)$	25.7	

As shown in Table II, ChatUniTest achieves higher coverage for two classes JSONObject and JSONArray. This discrepancy can be attributed to the fact that many methods in JSONObject and JSONArray are simple getter methods [69]. This allows ChatUniTest to easily generate valid tests by invoking these getter methods on JSONObject or JSONArray instances. While these tests contribute to coverage, they primarily focus on retrieving data immediately after object initialization and do not deeply exercise the functions or identify more complex issues. In contrast, tests from JSONTESTGEN are derived from issue-relevant unit tests, which may not include getters of all data types, as only common getters tend to appear in issue reports.

Constrastively, JSONTESTGEN achieves higher coverage scores in classes JSONPath and JSON. ChatUniTest struggles with long methods due to its reliance on including source code in prompts for LLM queries, which often results in throwing an "Exceed max prompt tokens" exception. Additionally, ChatUniTest faces challenges in generating tests for methods with complex usage scenarios, such as the overloaded parse methods with various arguments in JSON and the more intricate methods in JSONPath, rather than simple getters. Consequently, it fails to produce enough valid tests that compile and execute successfully for JSON and JSONPath.

In terms of bug detection, Zest identifies a bug documented in issue 2998 [70]. For ChatUniTest, we run the unit tests under the same setting outlined in Section III-E, which discovers a bug reported in issue 2997 [71]. JSONTESTGEN successfully identifies eight bugs, ranging from issue 2520 to 2536².

In conclusion, while ChatUniTest is effective at generating tests for basic classes and achieving decent coverage scores, it struggles with long methods and complex scenarios. Moreover, it only preserves tests that pass successfully, ignoring tests that fail due to bugs within the library, potentially overlooking defects. On the other hand, JSONTESTGEN avoids reliance on large source code bases and are able to identify hidden bugs as demonstrated in Section V-C.

Answer to RQ1. JSONTESTGEN achieves comparable or superior coverage scores and proves more effective at discovering bugs compared to state-of-the-art test generation tools.

B. RQ2: Ablation Study

1) Effects of Self-Generated Summarization: To investigate the effects of integrating self-generated summarization during

TABLE IV
COVERAGE RESULTS OF DIFFERENT LLMS (%)

	Instruction	Branch
t _{Llama3} w/o t _{original}	36.62	28.01
$t_{ m GPT-3.5}$ w/o $t_{original}$	45.63	36.16
$t_{\rm Llama3}$ w/ $t_{original}$	49.17	39.66
$t_{ m GPT-3.5}$ w/ $t_{original}$	49.10	39.67
$t_{original}$ alone	48.35	38.87



Fig. 3. Counts of detected bugs for Llama3-8b and GPT-3.5

test generation, we randomly sample 50 tests from our collected unit tests (Section III-A) and ask GPT-3.5 Turbo to generate three new tests for each of the sampled tests given as example, with and without the LLM-generated summarization (Section III-B).

Table III shows that tests generated with LLM-generated summarization have a slightly higher pass rate (56.3% vs. 54.2%) compared to tests without summarization. However, it significantly decreases the compile error rates from 25.7% to 13.9%. Manual review shows that tests without summarization often fail to compile due to missing bean class definitions, import statements, or hallucinated methods. Although the failure rate is higher with summarization (29.8% vs. 20.1%), both passing and failing tests are valuable for coverage and differential testing in bug detection. Therefore, the higher compile success rate when adding summarization is beneficial, as it leads to more syntactically correct tests for large-scale testing and bug identification.

2) Performance Variance of Different LLMs: To evaluate the effects of JSONTESTGEN with different LLMs, we experiment with an open-source LLM Llama3, and a commercial one GPT-3.5. Both models are configured with a top-p of 0.95 and a temperature of 0.8. We ask each of them to generate three tests for each of the original bug-triggering unit tests.

The coverage results of the generated tests (without adding mutation rules to the prompts) are shown in Table IV. Among them, Llama3 achieves a lower coverage than GPT-3.5 when excluding the original tests $t_{original}$. The reason is that the former suffers from a higher compile error rate of 25.7% compared to the latter's, which is 13.8%. Manual inspection reveals that tests generated by Llama3 often fail earlier in the code (compared to those by GPT-3.5), leaving the remaining code unexecuted. Additionally, certain new tests cannot be generated because some large $t_{original}$ exceed Llama3's context window length. Both models achieve similar coverage when considering all $t_{original}$, indicating that the original unit tests predominantly determine the final coverage. Alternatively, the newly generated code covers additional parts of the source code, albeit minimally, but is able to identify new bugs.

Figure 3 shows the overlaps between the bugs triggered by different LLMs (from the $681 \times 3 \times 2 = 4086$ total generated

²https://github.com/alibaba/fastjson2/issues?q=author:Cooper-Zhong

TABLE V
COVERAGE RESULTS OF APPLYING MUTATIONS (%)

	Instruction	Branch
t _{plain} w/o toriginal t _{mutate} w/o t _{original} t _{plain} w/ t _{original} t _{mutate} w/ t _{original} t _{original} alone	45.63 42.36 $49.10 (0.75 \uparrow)$ $49.87 (1.52 \uparrow)$ 48.35	36.16 32.86 $39.67 (0.80 \uparrow)$ $40.31 (1.44 \uparrow)$ 38.87



Fig. 4. Counts of detected bugs with and without mutations

test cases). The generated tests produce 121 inconsistencies that are manually verified. Overall, GPT-3.5 discovers more bugs than LLama3, while LLama3 identifies two unique bugs that GPT-3.5 fails to trigger. This demonstrates that combining results from different models can enhance bug detection. While LLMs vary in overall performance [72], differences in their training data, pre-training, and fine-tuning allow them to identify unique, non-overlapping functional defects [73]. We believe larger open-source LLMs could further improve results [74], but due to hardware limitations, we leave this exploration for future work.

3) Effectiveness of Mutation Strategies: To evaluate the effectiveness of applying mutation strategies, one of the five predefined rules (Section III-C) is randomly selected to prompt GPT-3.5 in each round of test generation. Same as Section V-B2, three tests are generated for each original test. We do not generate tests using all mutation rules because some of them may not be applicable in the context of $t_{original}$ (e.g., no bean class involved). Additionally, randomness is preserved, as even the same rule can produce different outputs due to the probabilistic nature of LLMs.

The results are presented in Table V. The tests generated without mutation prompts are $t_{\rm plain}$, while those generated with mutation prompts are labeled $t_{\rm mutate}$. When excluding $t_{\rm original}$ (w/o $t_{\rm original}$), we observe higher coverage for $t_{\rm plain}$. This is because 37.6% of $t_{\rm mutate}$ fail to compile, compared to only 13.8% for $t_{\rm plain}$. Consequently, $t_{\rm plain}$ contain more valid unit tests, resulting in higher coverage. When including $t_{\rm original}$ (w/ $t_{\rm original}$), $t_{\rm mutate}$ achieves slightly higher branch coverage.

Both prompts can identify bugs as seen in Figure 4. The detected bugs without mutation are those found by GPT-3.5 in Figure 3. We observe that both prompts, p_{plain} (without mutation rules) and p_{mutate} (with mutation), are capable of identifying unique bugs, with three bugs overlapping in between. Additionally, five unique bugs are identified by t_{plain} and four unique bugs are identified by t_{mutate} . We find that the LLM tends to make more conservative changes to the original tests with p_{plain} , resulting in the detection of certain unique bugs. In contrast, the LLM induces relatively larger changes with p_{mutate} , thereby discovering additional distinct bugs. This suggests that incorporating different mutation strategies into

the prompts can help uncover distinct bugs that the base setting alone might miss. However, p_{mutate} has a higher probability of generating semantically incorrect test programs, potentially missing some bugs that t_{plain} would detect. Motivated by this finding, we will try automatically repairing such test programs in the future.

Answer to RQ2. Self-generated summarization reduces the compile error rate, while JSON-specific mutation rules help uncover unique bugs that the base prompt may miss. Additionally, JSONTESTGEN can be adapted for use with different LLMs.

C. RQ3: Case Study of Detected Bugs

Besides the previous experiments, we have also continuously run JSONTESTGEN to fully test the *fastjson2* project. As of the end of June, JSONTESTGEN has discovered 34 real bugs in *fastjson2* and *fastjson-compatible*, with a total API cost of less than \$50. We do not report bugs for *fastjson* due to its infrequent maintenance. Here we present three typical examples of bugs discovered in *fastjson2*.

Listing 1. A bug in the JSONPath class

Listing 1 shows an example of inconsistency bug in JSONPath. The .eval() method produces different results when processing JSONObject and String, even though they contain the same JSON data. This case leads to a failed assertion at line 4. The bug has been reported in *fastjson2* issue 2584. The original test behind Listing 1 can be found in issue 1965. It only checks for null values of the JSONPath's evaluation results. In contrast, the test from JSONTESTGEN directly compares the evaluation results on both the original JSONObject and the serialized string. Although this test is generated without an explicit mutation rule, JSONTESTGEN still makes a meaningful modification that successfully triggers an inconsistency bug.

Listing 2. A serialization bug with Boolean type

Listing 2 illustrates a serialization bug involving the Boolean wrapper class. A method is called to serialize an object whose non-string values should be written as strings, enclosed in quotation marks. *Fastjson2* fails at line 3 with output {"b":true}, where the Boolean value is not quoted. This bug is confirmed and discussed in issue 2560. Listing 2 is generated from the test described in issue 1874. JSONTESTGEN switches a different configuration option WriteNonStringValueAsString instead of the

original WriteBooleanAsNumber. By applying Rule 4 in Section III-C, the new test reveals a serialization defect.

Listing 3. A deserialization bug with BigDecimal

Listing 3 demonstrates a descrialization bug with <code>BigDecimal</code>. When attempting to parse a JSON string into a <code>BigDecimal</code>, the <code>parseObject</code> method incorrectly interprets it as -9223372036854775808, resulting in a failed assertion at line 7. This issue is documented in <code>fastjson2</code> issue 2582. The original test case behind this bug is provided in issue 1204. JSONTESTGEN employs an alternative <code>parseObject</code> method, which exposes a descrialization bug due to an overflow error.

We have identified diverse types of bugs with JSONTEST-GEN, relating to annotations, (de)serialization, JSONPath, etc. A total of 34 bugs have been confirmed, with 30 of them fixed in the latest release of *fastjson2*. The full list of reported bugs can be found in *fastjson2*'s issue tracking system². The analysis of changes between the original and newly generated unit tests demonstrates that LLMs can effectively expand the diversity of the original test cases and thus uncover new bugs.

Answer to RQ3. JSONTESTGEN is effective for finding real world bugs by generating new unit tests that cover various functions of *fastjson2*, showcasing practical value in applications.

VI. RQ4: FAILED TEST ANALYSIS

A. Causes for Test Failures

```
String str = "[{\"name\":\"mask\"}]";
JSONArray array = JSON.parseArray(str);
Map object = array.getObject(0, Map.class);
assertNotNull(object);
assertEquals(0, object.size());
```

Listing 4. An example of incorrect test case

A failed unit test does not necessarily indicate a bug but may instead result from logically incorrect code. Listing 4 illustrates this issue: it erroneously asserts that the size of the extracted object is 0, whereas it should be 1 (line 5). In Section V-B3, among all generated tests that compiled, 67.0% successfully pass, 25.6% fail at assertions, and 7.4% crash due to exceptions or errors. We randomly sample 80 unit tests that fail or throw exceptions and manually review their root causes.

The top three exceptions thrown by them are: JSONException, NullPointerException, and ClassCastException. The primary cause is that parsing an incorrect JSON string, either syntactically incorrect or mismatched with the bean definition, directly results in a library-defined JSONException. Other reasons include calling parsing/serializing functions with incorrect parameters,

TABLE VI ACCURACY OF GPT-40'S CLASSIFICATION (%)

	E_{bad}	E_{good}	F_{bad}	F_{good}	avg.
FS	70.0	40.0	90.9	83.3	72.1
FS-CoT	50.0	50.0	90.9	83.3	69.8

casting data to incompatible types, and invoking methods on a null object.

For tests that fail at assertions, the most common cause is asserting contradictory values. This includes scenarios such as:

- After (de)serialization, expecting a value different from the previous object or the original JSON string (e.g., Listing 4).
- Expecting field names that contradict the bean fields.
- Wrongly assert a null or non-null object.
- Asserting incorrect data types.

Our experiment reveals that LLM-generated code can also be erroneous, underscoring the need for improved code quality and better filtering of false-positive failures.

B. Failed Test Classification via LLM

As an LLM-generated test can fail due to logically incorrect code, we hereby present an empirical experiment on whether LLMs can provide further justifications for failed unit tests. We begin with definitions of two types of test results, which are inspired by [75]:

Definition 1 (Good Test). A good test fails (at assertions or by throwing an exception) due to intrinsic bugs in the library (in this paper, fastjson2). The logic of a good test is considered correct.

Definition 2 (Bad Test). A bad test fails due to incorrect test code or improper usage of the library, indicating that the library is functioning as expected and the test case itself contains deficiencies.

Listing 1, 2 and 3 are examples of good tests that reveal real bugs. Conversely, Listing 4 is a bad test, since it erroneously asserts that the size of the extracted object is 0, whereas it should be 1.

We manually collect 43 unit tests from the generated test cases. Among them, 10 bad tests triggered exceptions (E_{bad}) , 11 bad tests failed at assertions (F_{bad}) , 10 good tests triggered exceptions (E_{good}) , and 12 good tests failed at assertions (F_{good}) . Instances of E_{good} and F_{good} are collected from the bugs we have identified, and we collect a similar number of E_{bad} and F_{bad} from the generated tests to ensure a balanced sample size. For each test instance, we use GPT-40 [58], one of the most capable reasoning LLMs, to classify it as either a good test or a bad test in both few-shot and few-shot plus chain-of-thought settings [38], [39]. Following the idea of [76], we employ a majority-voting method across 6 generations to determine the final classification labels (good or bad). The complete prompt template is in Figure 5.

The results are shown in Table VI. To our surprise, the few-shot with chain-of-thought (FS-CoT) approach, which includes reasoning steps in the few-shot examples (2 good tests and

2 bad tests), performs similarly to the basic few-shot (FS) method. For instances that throw an exception (E_{bad} and E_{good}), the performance is akin to random guessing. However, for instances that fail at assertions (F_{bad} and F_{good}), GPT-40 demonstrates a stronger ability to distinguish between them. We hypothesize that this is because GPT-40 can better infer code behaviors, but it still struggles to judge library-defined exceptions (e.g., JSONException for fastjson2) as these can result from both illegal inputs (bad) and library's issues (good).

Among all misclassified instances for FS and FS-CoT, 78% of them are overlapped. Many of these misclassifications are related to specific behaviors of *fastjson2*. These behaviors are indeed difficult to judge, and even experienced *fastjson2* users find it challenging to accurately assess them. Thus, even with reasoning steps, it is still difficult to judge a new case without prior experience. Nevertheless, our observation suggests that LLMs have the potential to classify bad test results, which should gain more future investigation.

Answer to RQ4. False-positive failures in LLM-generated tests for *fastjson2* primarily arise from parsing errors, mismatched bean definitions, incorrect parameters, and logical contradictions in assertions. While LLMs like GPT-40 show better performance in identifying assertion-related failures, they struggle to distinguish between user errors and actual library issues.

VII. DISCUSSIONS

A. Limitations and Future Work

One limitation is that JSONTESTGEN discards test cases that fail to compile, which reduces the number of valid cases and may result in losing potentially valuable tests. To mitigate this, we could enhance the quality and reliability of LLM-generated test cases by using more fine-grained domain knowledge-aware prompts [73]. This includes providing more precise and detailed API documentation, which is increasingly feasible as many LLMs now support longer context inputs [77]. Additionally, we could leverage automatic program repair, such as LLM self-debugging, to fix issues in the generated test cases [18], [51].

JSONTESTGEN also requires existing bug-triggering tests, which may not be available for smaller or newer projects. However, existing approaches can assist in generating unit tests, helping these projects build a robust suite of high-quality test cases [23], [25]. As development progresses, it is also expected that these projects will accumulate more tests over time.

In industrial settings, confidentiality concerns make it impractical to query closed-source LLMs with the original source code of commercial software. However, deploying larger open-source LLMs locally offers a promising solution for scaling testing in industry [29], [74].

False positives in test failures, caused by issues in LLM-generated code, are also common. To address this, JSON-TESTGEN employs differential testing as the test oracle,

```
I have several unit test cases for the library
fastjson2 that failed or produced errors. Some of
 these test failures do not reveal problems
within the [fastjson2] library, as the code logic
 of these failed tests is incorrect (e.g., wrong
assertions or improper usage of the library).
We categorize these tests into two types based on
 the following definitions:
<definitions>
I will give you a test case, you task is to
assess and judge whether the test case is a good
test or a bad test. Here are some examples:
[example 1]
[import statements]
public class TestExample1 {
    assertEquals(-2.0089457919266330204e-15,
             JSON.parseObject("{\"V\":
-2.0089457919266330204e-15}").get("V"));
    // failed here
    assertEquals(-2.0089457919266330204e-15,
             JSON.parseObject("{\"V\":
-2.0089457919266330204e-15}").getString("V"));}
[result 1]
Test set: TestExample1 <<< FAILURE!</pre>
org.opentest4j.AssertionFailedError: expected:
java.lang.Double@3366a998<-2.008945791926633E-15>
but was: java.lang.String@3c0403a
<-2.008945791926633E-15> at TestExample1.test(
TestExample1.java:17)
[answer 1(CoT)]
The test reports a failure because the assertion
is incorrect, expecting a Double but getting a
String. The revelant code is 'JSON.parseObject
("{\"V\": -2.0089457919266330204e-15}").getString
 "V")'. The code use 'getString' method to get
the value of key 'V' as String, but expecting a Double. The code logic is incorrect and it should
 be fixed to use 'getDouble'. Therefore, this
test is a bad test.
 answer 1(no CoT)]
The code logic is incorrect. Therefore, this test
 is a bad test.
<example 2, result 2, answer 2>
<example 3, result 3, answer 3>
<example 4, result 4, answer 4>
<example and result to judge>
<vour anwser>
```

Fig. 5. Prompt template for test failure classification

following similar approaches used in FuzzGPT [20] and JIT-Picker [78]. However, differential testing requires multiple implementations of the same specification, which can be difficult to find in certain contexts. In future work, we plan to explore test migration [79] as a way to facilitate differential testing. This would involve comparing semantically equivalent tests across various JSON libraries. The challenge here lies in the differences between library APIs—some APIs have direct counterparts in other libraries, while others are specific to a particular library, lacking equivalent functionality elsewhere.

Another possible solution is to use LLMs with strong

reasoning capabilities as post-test failure classifiers, as we examine through an empirical experiment in Section VI-B. While unit tests provide a test oracle through assertions, LLM-generated tests can be prone to errors [45]. With the advancement of LLMs that possess enhanced reasoning abilities, like OpenAI's o1 [80], we anticipate improvements of these models in classifying test failures. Our future goal is to integrate LLM-generated unit tests with a reasoning model to form a joint test oracle, further enhancing the testing process and generalizability across different JSON libraries or serialization formats.

B. Threats to Validity

The main threats to validity include the stability of LLMs and the testing environment for the generated code. To assess the usefulness of LLMs, we experiment with both an open-source LLM (Llama3) and a proprietary LLM (GPT-3.5). To ensure stable output, we fix the generation parameters such as temperature and top-p sampling, and use a specific version of GPT-3.5 Turbo (gpt-3.5-turbo-0125). Besides, our experiments are conducted in a standard Java environment, without testing on Android or Kotlin, thus we do not identify bugs on these platforms.

VIII. RELATED WORK

A. Fuzzing Libraries

Fuzzing plays a crucial role in ensuring software security and stability [61], [81]. Traditional fuzzers generate inputs for programs under test, such as strings for JSON parsers [61]. For example, the JSON fuzzer for fastison2 [11] in OSS-Fuzz [8] targets a specific parsing method, while EvoGFuzz [10] generates inputs for eight JSON parsers to uncover defects. However, these approaches focus on a limited set of predefined parsing methods rather than testing the entire library. When fuzzing libraries, it is often more effective for fuzzers to generate complete code or fuzzing harnesses that cover a broader range of critical library APIs. For instance, FuzzGPT [20] and TitanFuzz [19] utilize LLMs to generate Python code for testing deep learning libraries. RULF [82] is an automated approach for generating fuzz targets in Rust libraries based on API dependency graph traversal. Additionally, Rahalkar presents a system that generates fuzzing harnesses for library APIs and binary protocol parsers by analyzing unit tests [83]. Chen et al. [9] present a general fuzzer designed to test libraries without necessitating domain-specific knowledge in creating fuzz drivers. Fuzz4All [17] is a LLM-based universal fuzzer for multiple programming languages. Prior work has not specifically targeted JSON libraries in practice, and our research aims to address this gap.

B. Unit Test Generation

A significant amount of research has focused on developing unit test generation techniques [40], [41]. For instance, Almasi et al. [15] explore the effectiveness of unit test generation tools in identifying real faults within a financial application. Recently, researchers have explored the effectiveness of LLMs

in this area. Siddiq et al. [27] explore zero-shot unit test generation, examining how well LLMs can produce accurate and clean tests. Yuan et al. [23] conduct an empirical study on ChatGPT's unit test generation abilities and introduce the ChatTester tool. TestGenEval [84] offers a large-scale benchmark for assessing the test generation capabilities of code generation models. Bhatia et al. [85] evaluate ChatGPT's performance in generating Python unit tests, while Yang et al. [26] assess open-source LLMs' capabilities in this area. TestPilot [24] is an LLM-based tool that generates unit tests for JavaScript methods within project APIs. ChatUniTest [25] provides an LLM-powered framework with user-friendly APIs for automated unit test generation. TestGen-LLM [29] uses LLMs to automatically improve existing human-written tests and has been deployed at scale in production at Meta. UT-Gen [28] combines search-based testing with LLMs to improve the understandability of generated unit tests. Previous studies have primarily concentrated on automatically generating unit tests and evaluating them on benchmark datasets [86], focusing on aspects like test correctness, readability, and code coverage. Some also investigate defect detection, which requires confirmed bugs and faulty versions of the system under test [26]. In contrast, our research emphasizes fuzzing fastjson2 using generated unit tests, which successfully uncovers previously unknown bugs.

IX. CONCLUSION

In this paper, we propose JSONTESTGEN, utilizing LLMs to generate unit tests for the popular JSON library *fastj-son2*. By leveraging historical bug-triggering unit tests, LLMs can generate new code to discover unknown bugs. The test generation can be further enhanced through prompting with mutation strategies. Focusing on comparing test results rather than intermediate program outputs allows for more efficient differential testing. We also explore the potential of using LLMs as test failure classifiers. JSONTESTGEN has successfully identified 34 real bugs in *fastjson2*, demonstrating its efficacy in industrial practice.

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