

# ProjDevBench: Benchmarking AI Coding Agents on End-to-End Project Development

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## Abstract

Recent coding agents can generate complete codebases from simple prompts, yet existing evaluations focus on issue-level bug fixing and lag behind end-to-end development. We introduce PROJDEVBENCH, an end-to-end benchmark that provides project requirements to coding agents and evaluates the resulting repositories. Combining Online Judge (OJ) testing with LLM-assisted code review, the benchmark evaluates agents on (1) system architecture design, (2) functional correctness, and (3) iterative solution refinement. We curate 20 programming problems across 8 categories, covering both concept-oriented tasks and real-world application scenarios, and evaluate six coding agents built on different LLM backends. Our evaluation reports an overall acceptance rate of 27.38%: agents handle basic functionality and data structures but struggle with complex system design, time complexity optimization, and resource management. Our benchmark is available at this <https://github.com/zsworld6/projdevbench>.

## 1. Introduction

Recent progress in large language models has enabled coding agents to participate in software development workflows that extend beyond generating individual functions or files. This allows both developers and users with no prior coding knowledge alike to provide high-level project requirements and rely on a coding agent to implement the majority of the system—a workflow sometimes referred to as *vibe coding*.

These workflows point to a growing expectation that coding agents should be capable of constructing and even execut-

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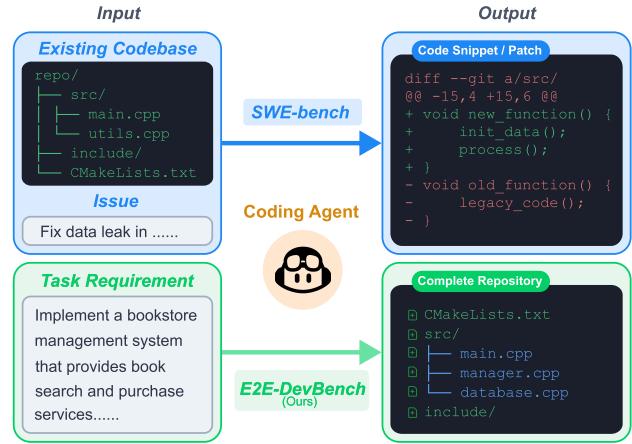


Figure 1. Task comparison. Unlike benchmarks where coding agents modify code snippets from pre-existing codebases based on issues or pull requests, our benchmark evaluates end-to-end repository construction directly from project-level requirements.

ing complete, runnable software at the project level. Given only an initial natural language specification, a coding agent is expected to autonomously determine the project structure, create and organize multiple source files, configure dependencies, and ultimately deliver a fully functional system (Figure 1 bottom). This setting emphasizes end-to-end project construction, where success depends not only on local code correctness but also on maintaining consistency across files, making coherent system-level design decisions, and ensuring the final system is fully executable.

Despite this shift towards end-to-end project construction, **most existing benchmarks for coding agents still focus on a smaller scale**: HumanEval (Chen et al., 2021) and MBPP (Austin et al., 2021) evaluate function-level code generation, while SWE-bench (Jimenez et al., 2024) and others study issue resolving in existing codebases (Figure 1 top). These benchmarks test an agent’s ability to understand or modify existing code to a certain extent, yet, they cannot reflect the competency of coding agents on end-to-end development tasks, which aim to construct complete projects from high-level specifications.

To address this gap, we propose **ProjDevBench**, a benchmark designed to evaluate coding agents on **end-to-end**

**Table 1.** Comparison with existing coding benchmarks. **From Scratch:** whether including tasks that require building a project without initial code or templates. **Output:** the granularity of expected submission. **E2E Exec.:** whether the benchmark requires building and running the complete system. **Diag. Feedback:** whether execution provides fine-grained diagnostic signals (e.g., error types, partial credit) beyond binary pass/fail. **Code Review:** specification-level compliance beyond testing.

Benchmark	From Scratch	Output	E2E Exec.	Diag. Feedback	Code Review
HumanEval / MBPP	✗	Function	✗	✗	✗
APPS / CodeContests	✗	Single-file	✗	✗	✗
RepoBench	✗	Repo (Partial)	✗	✗	✗
SWE-bench	✗	Patch	✗	✗	✗
DevEval	✓	Repository	✗	✗	✗
E2EDevBench	✓	Repository	✓	✗	✓
InnovatorBench	✗	Research Artifacts	✓	✗	✗
<b>ProjDevBench (Ours)</b>	✓	Repository	✓	✓	✓

**project construction.** In terms of requirements or input to the coding agents, ProjDevBench includes tasks where agents receive only simple high-level instructions without any initial codebase, in contrast to existing benchmarks that provide complete repository structures (Jimenez et al., 2024; Liu et al., 2024) or staged reference materials (Li et al., 2024) alongside requirements. In terms of expected outputs from the coding agents, instead of single-file updates (Chen et al., 2021; Austin et al., 2021) or atomic fixes (Jimenez et al., 2024), agents are required to generate full software repositories that can be executed in practice. We show a detailed comparison between ProjDevBench and existing benchmarks in Table 1.

We employ two complementary metrics to evaluate complete repositories generated by agents. First, we assess functional correctness through automated execution on an Online Judge (OJ) platform, which compiles, runs, and tests submissions against comprehensive test suites, and finally provides detailed diagnostics on failure modes. Second, since OJ evaluation alone cannot detect rule violations or cheating solutions, we introduce a code review mechanism that combines rule-based Python scripts for explicit constraint violations (e.g., forbidden library usage) with LLM-based review for subtler compliance issues.

A diverse set of tasks drawn from realistic programming scenarios is included in our ProjDevBench, enabling systematic evaluation of coding agents on their ability to plan, implement, and integrate components at the project level, effectively pushing the frontier of autonomous software development. Specifically, we curate 20 problems across 8 categories from coding concepts to real-world applications. These tasks demand extended interaction, with agents averaging 138 interaction turns and 4.81M tokens per problem in our experiments.

Our evaluation on six coding agents built on different LLM backends reveals several key findings: (1) Model performance varies significantly across tasks and models: Codex (OpenAI, 2025) with GPT-5 (Singh et al., 2025) achieves the best overall performance (77.85%), with performance gaps

widening on from-scratch construction tasks; GPT-5 generally excels at execution score while Sonnet-4.5 (Anthropic, 2025b) shows stronger code review and specification compliance; (2) Agents struggle with multiple critical aspects: specification alignment, edge case handling, time complexity optimization, and resource management, with 42% of failures attributed to wrong answers and 14% to time limits; (3) Extended interaction indicates difficulty and correlates negatively with performance, suggesting agents struggle to convert prolonged debugging into progress.

The contributions of our work are as follows:

- We introduce ProjDevBench, a benchmark for evaluating coding agents on end-to-end project construction, which includes autonomous design, build configuration, and strict performance constraints.
- We establish a dual evaluation protocol combining Online Judge (OJ) for execution-based correctness assessment with LLM-assisted code review for rule violations and cheating solutions detection.
- We provide comprehensive empirical analysis on 6 coding agents across 6 LLM backends, revealing systematic failure modes in specification alignment, edge case handling, complexity optimization, resource management, and multi-turn interaction patterns.

## 2. Related Work

**AI Coding Agents.** Modern coding agents span a spectrum of autonomy and integration modes. **IDE-integrated assistants** such as GitHub Copilot (GitHub, 2021) and Cursor (Cursor, 2023) provide real-time code suggestions within development environments, with newer versions incorporating increasing agent capabilities for multi-file editing and contextual understanding. **Autonomous frameworks** such as OpenHands (Wang et al., 2025) and CodeAgent (Zhang et al., 2024a) can independently operate terminal tools, manage file systems, and execute multi-

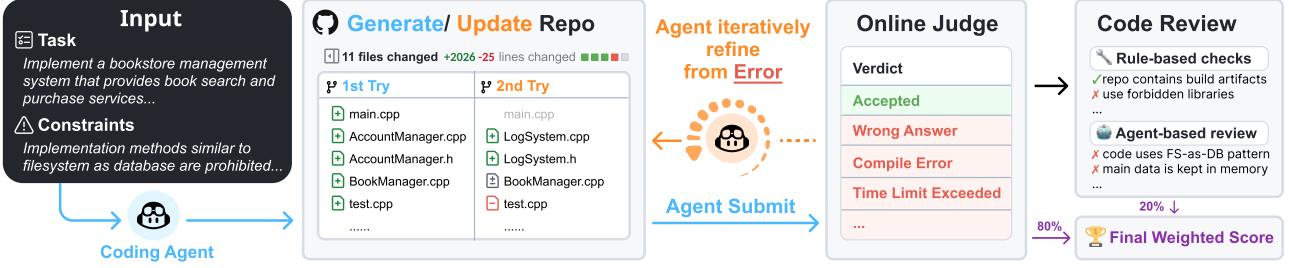


Figure 2. Overview of the benchmark pipeline.

step workflows. Recent research has explored specialized agent-computer interfaces for software engineering (Yang et al., 2024), simpler non-agenetic approaches (Xia et al., 2024), and autonomous program improvement (Zhang et al., 2024b). While these agents increasingly enable code coding, their ability to handle complex system-level decisions, build configurations, and from-scratch project construction remains under-explored in structured evaluations.

**Evolution of AI-Assisted SE Tasks.** Software engineering tasks for LLMs have shifted in granularity. Initial research focused on **function-level synthesis** and **repository-level completion** (Zhang et al., 2023; Liu et al., 2024), where models fill in missing logic within a predefined context. More recently, the focus has moved to **software maintenance**, such as bug fixing in SWE-bench (Jimenez et al., 2024), which requires generating patches for existing code. Agent frameworks have been enhanced through reasoning-acting paradigms (Yao et al., 2023), executable code actions (Wang et al., 2024), and iterative self-refinement (Madaan et al., 2023). However, **end-to-end project construction** remains a distinct challenge. Unlike maintenance, it requires agents to autonomously design directory structures, manage inter-file dependencies, configure build systems (e.g., CMake) without a pre-existing template, and autonomously run the project for testing. Crucially, such tasks demand **extended agent-environment interaction**—iterative cycles of code generation, execution, and refinement—that single-shot or limited-turn evaluations cannot capture.

**Code Generation Benchmarks.** Existing benchmarks primarily target specific stages of the development cycle but fall short of evaluating holistic project construction. Early benchmarks like HumanEval (Chen et al., 2021) and MBPP (Austin et al., 2021) are limited to single-function snippets. Competition-level benchmarks such as APPS (Hendrycks et al., 2021) and CodeContests (Li et al., 2022) evaluate algorithmic problem-solving but remain single-file tasks. Repository-level benchmarks are often patch-based, such as SWE-bench (Jimenez et al., 2024), which evaluates bug fixing in existing codebases, and RepoBench (Liu et al., 2024), which focuses on code completion within existing

repositories. Moreover, most existing benchmarks adopt single-shot evaluation, where a model generates code in one pass without iterative refinement.

Recent work has begun exploring end-to-end evaluation. DevEval (Li et al., 2024) decomposes development into staged tasks with reference inputs such as UML diagrams provided at each phase, but does not require fully autonomous construction. E2EDevBench (Zeng et al., 2025) evaluates agents on software development with hybrid test-case and LLM-based verification, focusing on PyPI package development. InnovatorBench (Wu et al., 2025) assesses agents on ML research automation with provided templates and scaffolds. However, these benchmarks primarily provide binary pass/fail feedback and focus on narrow domains, limiting their ability to capture diverse real-world software engineering challenges, including strict resource constraints and complex system-level design.

### 3. ProjDevBench

As shown in Figure 2, we design an end-to-end benchmark pipeline for coding agents, where an agent is given task descriptions and constraints in natural language, and is required to autonomously construct and iteratively refine a complete code repository. Each submission is evaluated through execution on an Online Judge, together with rule-based and LLM-based code review, and all evaluation signals are aggregated into a final weighted score.

#### 3.1. Task Definition and Scope

**Model input.** For each task, the agent is provided with a problem specification written in natural language. The specification describes the expected functionality, input and output formats, constraints, and submission requirements. For tasks in the *project-completion setting*, a partial codebase is provided as part of the input, representing an incomplete project that must be completed; for tasks in the *project-creation setting*, no initial codebase is provided, and the agent is required to implement the entire project from scratch based solely on the specification.

While our primary focus is on evaluating an agent’s abil-



Figure 3. Problem collection and filtering.

ity to construct complete software projects from scratch, we include both settings to enable controlled comparisons between project creation and project completion under a unified project-level evaluation objective; for analysis purposes, tasks in the project-completion and project-creation settings are categorized as *Easy* and *Hard* subsets, respectively.

**Model output.** The primary output of an agent is a software project rather than a code fragment. For most tasks, this output takes the form of a Git repository containing multiple source files, a valid build configuration (e.g., a `CMakeLists.txt`), and an executable that can be compiled and run successfully. Thus, correctness depends not only on implementing the required logic, but also on producing a coherent and buildable project that satisfies all task requirements. In fact, human reference solutions are non-trivial, typically consisting of multiple interacting files, with an average of around ten source files per project.

### 3.2. Problem Collection

We curate problems for ProjDevBench using a three-stage pipeline designed to emphasize end-to-end software construction rather than isolated algorithmic tasks.

**Stage I: Initial collection.** We collect approximately 2,800 candidate problems from a large-scale Online Judge platform used in undergraduate computer science education. This platform hosts both traditional algorithmic problems similar to competitive programming and course assignments that require building complete, multi-file software systems.

**Stage II: Scope-based filtering.** We retain problems that involve project-level development, such as multi-file implementations, explicit module organization, build system configuration (e.g., `CMakeLists.txt`), reusable abstractions, or stateful multi-command interfaces. Purely algorithmic or single-function tasks are excluded, reducing the candidate set to approximately 100 problems.

**Stage III: Quality-based filtering.** We further select problems with clear specifications, comprehensive test suites covering both functionality and edge cases, and non-trivial difficulty as reflected by historical submission outcomes. Problems with test vulnerabilities or shortcut solutions are removed, yielding the final set of 20 problems.

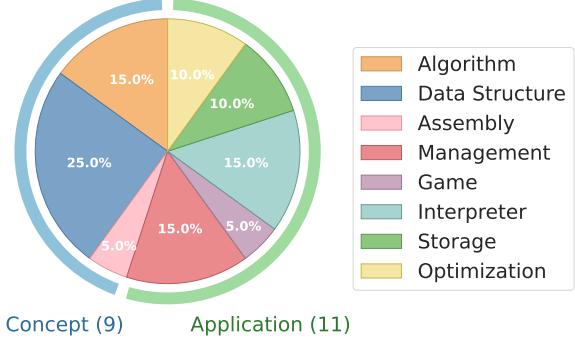


Figure 4. Distribution of ProjDevBench tasks across 8 categories.

Through this process, we obtain 20 problems covering a range of realistic software development scenarios, including data structures, interpreters, management systems, and storage components. Domain experts then reformulate the original problem statements into standardized task descriptions suitable for agent evaluation. Detailed task-level statistics and problem attributes are provided in Table 5, with the distribution of task categories summarized in Figure 4.

### 3.3. Evaluation Protocol

ProjDevBench adopts a dual evaluation protocol that distinguishes between hard functional correctness and compliance at the rule level and specification level.

**Execution-based evaluation.** All submissions are evaluated using comprehensive test suites on the Online Judge platform. Test cases verify end-to-end executability, functional correctness, edge-case handling, and compliance with problem-specific time and memory limits. Each submission receives an *Execution Score* computed as a weighted sum of passed test cases, where individual test points may carry different score weights reflecting their relative importance or difficulty. In contrast to binary pass/fail evaluation in prior work (Zeng et al., 2025), the Online Judge provides *fine-grained verdict-level failure signals*—including compile errors, runtime errors, time limit exceeded, memory limit exceeded, and wrong answer verdicts—that enable systematic diagnosis of agent failure modes and support iterative debugging, as demonstrated in Section 5.

**Code review.** In addition to OJ testing, ProjDevBench performs code review to assess whether a submission genuinely

follows the problem specification. This evaluation focuses on criteria that cannot be reliably captured by test cases, including violations of explicit problem rules (e.g., forbidden libraries), hack-based or adversarial solutions, and implementations that exploit weaknesses in the test suite rather than adhering to the intended constraints. Each submission receives a *Code Review score* reflecting its compliance with these requirements. We employ an LLM-based code review approach to judge such specification-level compliance.

**Final scoring.** The final score is computed as a weighted combination of the OJ score and the Code Review score, with functional correctness accounting for the majority of the weight. This design prioritizes producing correct and executable solutions while penalizing submissions that violate essential requirements or problem constraints.

## 4. Experiments

### 4.1. Experimental Setup

**Agents and Models.** We evaluate six coding agents via their command-line interfaces: **Cursor** (Cursor, 2023), **GitHub Copilot** (GitHub, 2021), **Claude Code** (Anthropic, 2025a), **Augment** (Augment, 2022), **Codex CLI** (OpenAI, 2025), and **Gemini CLI** (Google, 2025). We test agents with frontier models **GPT-5** (Singh et al., 2025), **Claude Sonnet 4.5** (Anthropic, 2025b), and **Gemini 3 Pro Preview** (Google DeepMind, 2025). GPT-5 and Sonnet-4.5 are evaluated across five agents, while Gemini 3 Pro is evaluated on Cursor, Copilot, and Gemini CLI. For Claude Code, we additionally evaluate open-source models **GLM-4.6** (GLM et al., 2024), **Kimi-k2-0905-Preview** (Team et al., 2025), and **DeepSeek-V3.2-Exp** (Liu et al., 2025).

**Implementation details.** For each agent-model configuration, we run a single evaluation pass on every problem in the benchmark. Each run is constrained by the maximum number of submissions allowed per problem (ranging from 2 to 18 depending on problem complexity), rather than a fixed time budget. All agents are evaluated using the same prompts and problem specifications to ensure fair comparison. The final score weighs execution correctness at 80% and code review compliance at 20%.

### 4.2. Main Results

Table 2 presents the execution, code review, and final weighted scores for each configuration. Our results answer the following three key questions.

**Which agent framework achieves the best overall performance?** Codex paired with GPT-5 achieves the highest final weighted score of 77.85, outperforming Augment+GPT-5 at 72.35, Cursor+GPT-5 at 71.85, and

Claude Code+Sonnet-4.5 at 68.87. This advantage stems primarily from its coding capabilities, where Codex+GPT-5 reaches 76.73 execution score compared to Augment+GPT-5’s 72.13. The difference becomes more pronounced on hard problems requiring from-scratch construction, where Codex+GPT-5 maintains 69.22 execution score versus Augment+GPT-5’s 57.22 and Cursor+GPT-5’s 67.80. Notably, Cursor+Gemini-3-Pro-Preview achieves 75.32, demonstrating competitive performance. Both Cursor and Augment demonstrate stable performance across different base models, with all their tested configurations achieving final scores above 70, suggesting their framework design is relatively stable regardless of the underlying language model choice.

### How do different base models affect agent performance?

Model selection exhibits notable interactions with agent framework design. For execution scores, GPT-5 generally outperforms Sonnet-4.5 across most frameworks, with the gap varying by framework. In Codex, GPT-5 achieves 76.73 versus Sonnet-4.5’s 57.52, while in Augment, GPT-5 reaches 72.13 compared to Sonnet-4.5’s 66.06. Gemini-3-Pro-Preview shows mixed results in execution score: it achieves 72.52 in Cursor (comparable to GPT-5’s 69.26) but only 53.53 in GitHub Copilot. The pattern differs for code review compliance: In Claude Code, Sonnet-4.5 achieves the highest code review score of 89.31, exceeding GPT-5’s 84.03, while Augment+Sonnet-4.5 scores 86.28 compared to Augment+GPT-5’s 73.26. Within the Claude Code framework, we also evaluate three open-source models, which achieve final scores of 52.77, 50.33, and 57.95 respectively. GLM-4.6 achieves the highest final score at 57.95, slightly surpassing GPT-5 at 57.34, while Kimi-k2-0905-Preview and DeepSeek-V3.2-Exp lag notably behind at 52.77 and 50.33. All open-source models remain behind Sonnet-4.5’s 68.87 final score, indicating a performance gap between open-source and the strongest closed-source models.

### How does problem difficulty affect agent robustness?

The transition from easy problems with partial codebases to hard problems requiring from-scratch construction reveals differences in framework robustness. Codex+GPT-5 maintains relatively stable execution performance, declining from 79.24 on easy problems to 69.22 on hard. Cursor+GPT-5 demonstrates similar stability with a drop from 69.74 to 67.80. In contrast, GitHub Copilot+Sonnet-4.5 shows substantial degradation, decreasing from 71.10 to 36.63, while Gemini CLI drops sharply from 74.57 to 35.53. Code review scores exhibit varied patterns: Cursor+GPT-5 increases from 80.56 to 87.27, and Codex+Sonnet-4.5 rises from 68.22 to 83.23, suggesting that specification compliance issues may manifest differently when agents modify existing codebases compared to constructing projects from scratch, potentially due to the complexity of understanding and integrating with

Table 2. Performance on ProjDevBench (“Exec.”: Execution; “CR”: Code Review; “Final”: Weighted Score)

Agent	Model	Easy (E)			Hard (H)			Overall		
		Exec.	CR	Final	Exec.	CR	Final	Exec.	CR	Final
Augment	GPT-5	77.10	76.00	76.88	57.22	65.03	58.78	72.13	73.26	72.35
	Sonnet-4.5	69.14	<b>92.56</b>	73.83	56.81	67.43	58.93	66.06	86.28	70.10
Codex	GPT-5	<b>79.24</b>	82.11	<b>79.81</b>	<b>69.22</b>	82.90	<b>71.95</b>	<b>76.73</b>	82.31	<b>77.85</b>
	Sonnet-4.5	66.07	68.22	66.50	31.88	83.23	42.15	57.52	71.98	60.41
Gemini CLI	Gemini-3-Pro-Preview	74.57	80.33	75.72	35.53	<b>94.20</b>	47.26	64.81	83.80	68.61
Cursor	GPT-5	69.74	80.56	71.90	67.80	87.27	71.69	69.26	82.23	71.85
	Sonnet-4.5	71.12	85.67	74.03	60.17	66.47	61.43	68.39	80.87	70.88
	Gemini-3-Pro-Preview	72.87	88.67	76.03	71.47	80.03	73.18	72.52	86.51	75.32
GitHub Copilot	GPT-5	59.79	71.11	62.06	55.20	82.90	60.74	58.64	74.06	61.73
	Sonnet-4.5	71.10	87.89	74.46	36.63	80.23	45.35	62.48	85.97	67.18
	Gemini-3-Pro-Preview	59.22	58.11	59.00	36.44	75.67	44.29	53.53	62.50	55.32
Claude Code	DeepSeek-V3.2-Exp	50.05	60.78	52.20	35.23	82.77	44.74	46.34	66.28	50.33
	GLM-4.6	56.25	80.89	61.18	39.22	84.37	48.25	52.00	81.76	57.95
	GPT-5	50.69	84.33	57.42	50.59	83.13	57.10	50.67	84.03	57.34
	Kimi-k2-0905-Preview	53.49	65.89	55.97	35.56	73.67	43.18	49.00	67.83	52.77
	Sonnet-4.5	66.85	92.89	72.06	54.47	78.57	59.29	63.76	<b>89.31</b>	68.87

Table 3. Distribution of submission status types across all agents.

Status Type	Count	Percentage
Accepted	484	27.38%
Wrong Answer	740	41.86%
Time Limit Exceeded	246	13.91%
Runtime Error	124	7.01%
Compile Error	80	4.52%
Memory Leak	62	3.51%
Memory Limit Exceeded	24	1.36%
Others	8	0.45%

pre-existing code structures and architectural decisions.

## 5. Analysis and Discussion

### 5.1. Where End-to-End Coding Agents Fail

Table 3 summarizes submission outcomes across all agents. Only 27.38% of submissions were accepted, with the majority failing due to wrong answers (41.86%) or time limit violations (13.91%). Rather than analyzing these statuses in isolation, we group them into higher-level failure modes based on their underlying causes, as discussed below.

**Specification misalignment.** Agents frequently fail due to misalignment between their understanding of problem specifications and actual requirements, evidenced by Wrong Answer and Compile Error submissions. Functional incompleteness appears when agents generate syntactically correct frameworks but omit critical business logic—in Train Ticket Management, all agents omitted the seat management system despite implementing user management and train querying. Similarly, in Minesweeper, agents accessed only

3,789 of 3,825 safe blocks, indicating incomplete implementation rather than logical errors. Structural misunderstanding manifests when agents fail to distinguish development from submission contexts: in int2048, agents included test code with `main()` functions, causing redefinition errors. Algorithmic understanding deviations also occur, as in Mini-Aidiv-N where agents implemented Softmax by summing entire matrices rather than row-wise, resulting in 0.02 accuracy despite runnable code.

**Edge case handling deficiencies.** Agents demonstrate systematic weaknesses in boundary condition handling, leading to both Wrong Answer and Runtime Error failures. Bookstore Hidden Test Points saw all agents fail, indicating struggles with edge cases like empty strings, file I/O exceptions, and nested scenarios. Runtime safety failures manifest at the test case level, with numerous Segmentation Faults and Aborted errors caused by null pointer dereferences and array bounds violations. In map implementation, Red-Black Tree implementations lacked proper null checks in rotation functions, while ICPC Management System had many test cases resulting in Aborted errors from uninitialized variables. Detail processing errors also appear: in Bookstore, agents used substring matching instead of exact keyword matching, causing “math” to incorrectly match “mathematics”.

**Time complexity analysis deficiencies.** Agents exhibit systematic weaknesses in time complexity reasoning, resulting in a substantial number of Time Limit Exceeded submissions despite functionally correct implementations. In the ICPC Management System, agents re-sorted all teams after each unfreeze operation, yielding an  $O(K \times N \log N)$  solution, whereas the correct approach exploits the locality

of ranking changes to achieve  $O(K \log N)$  using ordered data structures. This failure reflects an inability to identify and leverage problem-specific structural properties.

More broadly, agents favor familiar but suboptimal patterns: they recompute global orderings instead of performing incremental updates, and frequently use `map` where key ordering is unnecessary, incurring  $O(\log N)$  overhead instead of  $O(1)$  average-case lookups with `unordered_map`. Similar inefficiencies appear in I/O handling, where unbuffered reads or excessive small writes further exacerbate performance issues. Together, these behaviors indicate that complexity analysis and performance optimization are not systematically integrated into agents' reasoning processes.

**Resource management limitations.** Agents exhibit significant limitations in managing computational resources, particularly exception safety and algorithmic efficiency, leading to Memory Leak, Runtime Error, and Time Limit Exceeded failures. Exception safety failures cause most memory leaks: in BASIC Interpreter, 25 submission cases occurred when `std::stoi()` threw exceptions after allocating `lhs` and `rhs` expressions, which were not released. Agents handle explicit error paths but fail to account for exceptions during normal operation, preferring manual `new/delete` over RAII patterns. Memory management errors in Runtime Errors further illustrate limitations: Mini-Aidiv-N had 21 submission cases from invalid matrix pointer access despite assertion checks, indicating incomplete defensive programming.

**Code engineering capability gaps.** Agents demonstrate systematic gaps in advanced C++ concepts and code organization, leading to Compile Errors and Runtime Errors. Template programming limitations appear in list implementation, where agents assumed template types would have default constructors, directly storing `T` data despite README warnings, causing failures with types providing only parameterized constructors. Namespace and header management issues appear where agents failed to properly merge files according to submission requirements. Code structure misunderstanding is reflected in Redefinition Errors where agents included test code in submission files, treating development and submission contexts as equivalent.

## 5.2. Insights from Code Review

Beyond execution outcomes, Code Review exposes agent behaviors related to version control, build configuration, and specification compliance that are invisible to execution-based evaluation. These findings highlight limitations in agents' understanding of software development as a structured workflow rather than a pure code generation task.

**Misunderstanding of version control workflow.** Agents frequently fail to treat version control as an essential part of task completion. In multiple cases, agents modified code locally and created commits but did not push changes to the remote repository, resulting in incomplete submissions visible only through local git history. This indicates that agents implicitly assume code writing alone constitutes task completion, overlooking the requirement that progress must be explicitly recorded and submitted through version control.

**Specification compliance failures.** Code Review reveals systematic failures to adhere to explicit submission specifications in a subset of cases. Agents sometimes misconfigure build systems, producing executables with incorrect names or including build artifacts in submissions. Coding standards are occasionally violated, such as using prohibited standard library headers or forbidden language constructs like `using namespace std`. Required files are sometimes omitted, and protected templates are modified despite explicit restrictions. They reveal a pattern where agents treat specification requirements as secondary to functional correctness, failing to recognize that complete task fulfillment requires strict adherence to all stated constraints, not just those that affect execution outcomes.

Overall, our Code Review analysis reveals systematic aspects of software development that are not captured by execution-based evaluation. Therefore, it serves as a complementary evaluation signal that surfaces important limitations beyond execution-level correctness.

## 5.3. Interaction Length and Performance.

ProjDevBench tasks involve extended multi-turn agent-environment interaction, with agents averaging 138 interaction turns and 4.81M tokens per problem. The most complex tasks require up to two hours to complete. To analyze how interaction behavior relates to task difficulty and performance, we conduct an analysis based on execution logs from Claude Code and five models. For each problem, we aggregate interaction statistics across models, including the number of interaction turns, total token consumption, and the final task score. In addition, we compute two static code-level complexity measures from human reference solutions: the number of relevant files and the net number of modified lines. Table 6 reports per-problem statistics, and Table 4 summarizes the corresponding Spearman rank correlations.

**Correlation between interaction length and performance.** Across problems, we observe a clear relationship between these two. Both the number of interaction turns and total token consumption are strongly negatively correlated with final scores (Spearman  $\rho = -0.668$  and  $\rho = -0.734$ , respectively). Problems that trigger prolonged interaction tend to

Table 4. Spearman Correlations among Variables.

Variable Pair	Spearman $\rho$	p-value
Tokens vs. Score	<b>-0.734</b>	0.0002
Turns vs. Score	<b>-0.668</b>	0.0013
Net Lines vs. Score	-0.341	0.1415
File Count vs. Score	-0.322	0.1665
File Count vs. Turns	0.413	0.0706
Net Lines vs. Turns	0.309	0.1848
Turns vs. Tokens	<b>0.898</b>	< 0.0001
Net Lines vs. File Count	<b>0.746</b>	0.0002

yield substantially lower performance, whereas easier problems are typically solved with fewer interaction turns and tokens, and achieve high scores. This indicates that task difficulty is closely reflected in the extent of agent–environment interaction, but extended interaction alone does not guarantee successful task completion.

**Turns and token usage.** We further observe a strong positive correlation (0.898) between interaction turns and token consumption, suggesting that increased token usage primarily results from repeated interaction turns rather than a small number of isolated long reasoning steps.

**Static code complexity.** In contrast, static code-level complexity exhibits only weak relationships with both interaction length and performance. While the number of files and net modified lines are strongly correlated with each other, their correlations with interaction turns and scores are moderate. This suggests that although file-level complexity captures certain aspects of problem structure, it does not sufficiently explain the variation in agent performance.

Overall, these results indicate that task difficulty in ProjDevBench manifests primarily through prolonged interaction and reduced performance, rather than being directly determined by static code size. Harder problems compel agents to engage in extended interaction, yet often still result in low final scores, highlighting a limitation of current agents in converting prolonged interaction into effective progress.

#### 5.4. Human Validation of LLM-Based Code Review

To assess the reliability of the LLM-based code review used in ProjDevBench, we compare model judgments with expert annotations. The code review process involves two kinds of judgments. The first assigns continuous scores to qualitative aspects of code, such as readability and organization. The second makes binary decisions on whether a submission violates explicit problem requirements. Multiple human annotators independently review the same submissions using the same criteria. Human judgments are aggregated by averaging continuous scores and by majority vote for binary

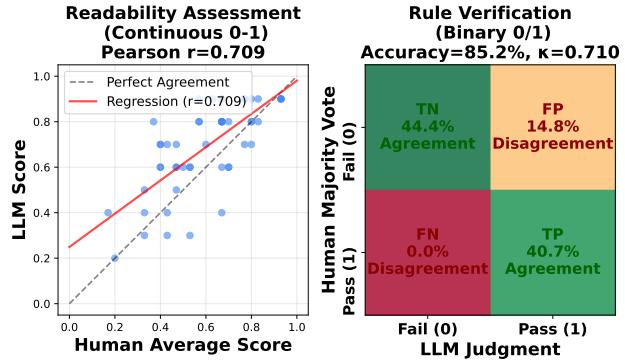


Figure 5. Human verification of LLM-based code review. **Left:** Correlation between the proposed LLM readability score and human scores. **Right:** Agreement on binary rule verification.

decisions, and are then compared against the corresponding LLM-based evaluations.

As shown in Figure 5, LLM-based code review aligns closely with human judgment. For continuous quality assessment, model scores show strong correlation with human ratings, indicating consistent relative evaluation of code quality. For binary rule verification, the LLM judge achieves high accuracy and substantial agreement with human annotations, as reflected by an accuracy of 0.852 and a Cohen’s  $\kappa$  of 0.710. These results indicate that LLM-based code review provides a reliable approximation of human judgment for enforcing specification-level requirements in benchmark evaluation, enabling scalable quality assessment.

## 6. Conclusion

In this paper, we introduced ProjDevBench, a novel benchmark designed to evaluate coding agents in the context of end-to-end project development. Our comprehensive evaluation of current frontier coding agents reveals that while they show promise for simple tasks, significant gaps remain in handling complex, real-world engineering constraints and system-level integration. By providing a diverse set of challenging tasks and a dual-mode evaluation, ProjDevBench establishes a more realistic standard for the next generation of autonomous software engineering agents.

## Limitations and Future Work

ProjDevBench currently includes 20 tasks. Scaling the benchmark is challenging due to the substantial effort required to curate project-level problems with clear specifications and robust test suites, especially for long-running agent sessions. Additionally, tasks focus primarily on C++, and it remains unclear whether observed agent behaviors generalize to other languages. Finally, our evaluation targets fully autonomous agents without human feedback, which isolates end-to-end capabilities but excludes human-in-the-

loop workflows; extending to interactive settings is a promising future direction.

## Impact Statement

This paper introduces a benchmark for evaluating AI coding agents on end-to-end software development. By providing standardized evaluation with diagnostic feedback and code review mechanisms, our work encourages the development of coding agents that produce correct, specification-compliant, and maintainable code. We believe rigorous benchmarking is a necessary step toward the responsible deployment of autonomous coding systems. We do not foresee specific negative societal consequences beyond those generally associated with advances in AI-assisted programming.

## References

- Anthropic. Claude code: An agentic coding tool. <https://docs.anthropic.com/en/docs/clause-code>, 2025a. Accessed: 2025.
- Anthropic. Claude sonnet 4.5: A hybrid reasoning model. *Anthropic Technical Report*, 2025b. URL <https://www.anthropic.com/news/clause-sonnet-4-5>.
- Augment. Augment code. <https://www.augmentcode.com>, 2022. Accessed: 2025.
- Austin, J., Odena, A., Nye, M., Bosma, M., Michalewski, H., Dohan, D., Jiang, E., Cai, C., Terry, M., Le, Q., et al. Program synthesis with large language models. *arXiv preprint arXiv:2108.07732*, 2021.
- Chen, M., Tworek, J., Jun, H., Yuan, Q., de Oliveira Pinto, H. P., Kaplan, J., Edwards, H., Burda, Y., Joseph, N., Brockman, G., Ray, A., Puri, R., Krueger, G., Petrov, M., Khlaaf, H., Sastry, G., Mishkin, P., Chan, B., Gray, S., Ryder, N., Pavlov, M., Power, A., Kaiser, L., Bavarian, M., Winter, C., Tillet, P., Such, F. P., Cummings, D., Plappert, M., Chantzis, F., Barnes, E., Herbert-Voss, A., Guss, W. H., Nichol, A., Paino, A., Tezak, N., Tang, J., Babuschkin, I., Balaji, S., Jain, S., Saunders, W., Hesse, C., Carr, A. N., Leike, J., Achiam, J., Misra, V., Morikawa, E., Radford, A., Knight, M., Brundage, M., Murati, M., Mayer, K., Welinder, P., McGrew, B., Amodei, D., McCandlish, S., Sutskever, I., and Zaremba, W. Evaluating large language models trained on code. 2021.
- Cursor. Cursor: AI-powered code editor. <https://www.cursor.so/>, 2023. URL <https://www.cursor.so/>. Accessed: 2025.
- GitHub. GitHub Copilot: Your AI pair programmer. <https://copilot.github.com/>, 2021. URL <https://copilot.github.com/>. Accessed: 2025.
- GLM, T., Zeng, A., Xu, B., Wang, B., Zhang, C., Yin, D., Zhang, D., Rojas, D., Feng, G., Zhao, H., et al. Chatglm: A family of large language models from glm-130b to glm-4 all tools. *arXiv preprint arXiv:2406.12793*, 2024.
- Google. Gemini cli, 2025. URL <https://github.com/google-gemini/gemini-cli>.
- Google DeepMind. Gemini 3: A new era of intelligence. <https://blog.google/products-and-platforms/products/gemini/gemini-3/>, 2025. Accessed: 2025.
- Hendrycks, D., Basart, S., Kadavath, S., Mazeika, M., Arora, A., Guo, E., Burns, C., Puranik, S., He, H., Song, D., and Steinhhardt, J. Measuring coding challenge competence with apps. *NeurIPS*, 2021.
- Jimenez, C. E., Yang, J., Wettig, A., Yao, S., Pei, K., Press, O., and Narasimhan, K. R. SWE-bench: Can language models resolve real-world github issues? In *International Conference on Learning Representations*, 2024. URL <https://openreview.net/forum?id=VTF8yNQM66>.
- Li, J., Li, G., Zhao, Y., Li, Y., Liu, H., Zhu, H., Wang, L., Liu, K., Fang, Z., Wang, L., et al. Deeval: A manually-annotated code generation benchmark aligned with real-world code repositories. *arXiv preprint arXiv:2405.19856*, 2024.
- Li, Y., Choi, D., Chung, J., Kushman, N., Schrittweiser, J., Leblond, R., Eccles, T., Keeling, J., Gimeno, F., Dal Lago, A., et al. Competition-level code generation with alphacode. *Science*, 378(6624):1092–1097, 2022.
- Liu, A., Mei, A., Lin, B., Xue, B., Wang, B., Xu, B., Wu, B., Zhang, B., Lin, C., Dong, C., et al. Deepseek-v3. 2: Pushing the frontier of open large language models. *arXiv preprint arXiv:2512.02556*, 2025.
- Liu, T., Xu, C., and McAuley, J. Repobench: Benchmarking repository-level code auto-completion systems, 2024. URL <https://arxiv.org/abs/2306.03091>.
- Madaan, A., Tandon, N., Gupta, P., Hallinan, S., Gao, L., Wiegreffe, S., Alon, U., Dziri, N., Prabhumoye, S., Yang, Y., Gupta, S., Majumder, B. P., Hermann, K., Welleck, S., Yazdanbakhsh, A., and Clark, P. Self-refine: iterative refinement with self-feedback. In *Advances in Neural Information Processing Systems*, NIPS ’23, Red Hook, NY, USA, 2023. Curran Associates Inc.

- OpenAI. Codex cli. <https://github.com/openai/codex>, 2025. Accessed: 2025.
- Singh, A., Fry, A., Perelman, A., Tart, A., Ganesh, A., El-Kishky, A., McLaughlin, A., Low, A., Ostrow, A., Ananthram, A., et al. Openai gpt-5 system card. *arXiv preprint arXiv:2601.03267*, 2025.
- Team, K., Bai, Y., Bao, Y., Chen, G., Chen, J., Chen, N., Chen, R., Chen, Y., Chen, Y., Chen, Y., et al. Kimi k2: Open agentic intelligence. *arXiv preprint arXiv:2507.20534*, 2025.
- Wang, X., Chen, Y., Yuan, L., Zhang, Y., Li, Y., Peng, H., and Ji, H. Executable code actions elicit better llm agents. In *International Conference on Machine Learning*, 2024.
- Wang, X., Li, B., Song, Y., Xu, F. F., Tang, X., Zhuge, M., Pan, J., Song, Y., Li, B., Singh, J., Tran, H. H., Li, F., Ma, R., Zheng, M., Qian, B., Shao, Y., Muennighoff, N., Zhang, Y., Hui, B., Lin, J., Brennan, R., Peng, H., Ji, H., and Neubig, G. Openhands: An open platform for ai software developers as generalist agents, 2025. URL <https://arxiv.org/abs/2407.16741>.
- Wu, Y., Fu, D., Si, W., Huang, Z., Jiang, M., Li, K., Xia, S., Sun, J., Xu, T., Hu, X., Lu, P., Cai, X., Ye, L., Zhu, W., Xiao, Y., and Liu, P. Innovatorbench: Evaluating agents' ability to conduct innovative llm research, 2025. URL <https://arxiv.org/abs/2510.27598>.
- Xia, C. S., Deng, Y., Dunn, S., and Zhang, L. Agentless: Demystifying llm-based software engineering agents. *arXiv preprint*, 2024.
- Yang, J., Jimenez, C. E., Wettig, A., Lieret, K., Yao, S., Narasimhan, K. R., and Press, O. SWE-agent: Agent-computer interfaces enable automated software engineering. In *Advances in Neural Information Processing Systems*, 2024. URL <https://arxiv.org/abs/2405.15793>.
- Yao, S., Zhao, J., Yu, D., Du, N., Shafran, I., Narasimhan, K., and Cao, Y. ReAct: Synergizing reasoning and acting in language models. In *International Conference on Learning Representations*, 2023.
- Zeng, Z., Li, Y., Xie, R., Ye, W., and Zhang, S. Benchmarking and studying the llm-based agent system in end-to-end software development, 2025. URL <https://arxiv.org/abs/2511.04064>.
- Zhang, F., Chen, B., Zhang, Y., Keung, J., Liu, J., Zan, D., Mao, Y., Lou, J.-G., and Chen, W. RepoCoder: Repository-level code completion through iterative retrieval and generation. In Bouamor, H., Pino, J., and Bali, K. (eds.), *Proceedings of the Conference on Empirical Methods in Natural Language Processing*, pp. 2471–2484, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.emnlp-main.151. URL <https://aclanthology.org/2023.emnlp-main.151>.
- Zhang, K., Li, J., Li, G., Shi, X., and Jin, Z. CodeAgent: Enhancing code generation with tool-integrated agent systems for real-world repo-level coding challenges. In Ku, L.-W., Martins, A., and Srikumar, V. (eds.), *Proceedings of the Annual Meeting of the Association for Computational Linguistics*, pp. 13643–13658, Bangkok, Thailand, August 2024a. Association for Computational Linguistics. doi: 10.18653/v1/2024.acl-long.737. URL <https://aclanthology.org/2024.acl-long.737>.
- Zhang, Y., Ruan, H., Fan, Z., and Roychoudhury, A. Autocoderover: Autonomous program improvement, 2024b. URL <https://arxiv.org/abs/2404.05427>.

## A. Problem Details

Table 5 summarizes the full set of tasks included in ProjDevBench. The table lists per-problem metadata, including category, submission format, resource constraints, and student performance statistics. These attributes are provided for reference.

**Table 5.** Detailed information for all 20 problems. **Category** indicates the problem domain (Algorithm, Management, Game, Interpreter, Assembly, Data Structure, Storage, or Optimization). **Difficulty** is rated as E (Easy) or H (Hard) based on whether an initial codebase is provided. **Submit** specifies the submission method: C++ for direct source code submission, Git for repository-based submission, or mov for assembly-only problems. **Tests** denotes the number of distinct OJ problem IDs associated with each task. **Time** and **Mem** show the maximum time limit (in seconds) and memory limit (in MiB) across all subtasks, respectively. **Avg Score** represents the average normalized score (0–100) achieved by participating students across all submissions.

ID	Problem Name	Category	Difficulty	Submit	Tests	Time (s)	Mem (MiB)	Avg Score
001	A+B Problem	Algorithm	E	Git	1	1	256	54.37
002	int2048 - Big Integer Arithmetic	Algorithm	E	C++	6	10	190	48.19
003	ICPC Management System	Management	H	Git	1	2	512	52.07
004	Bookstore Management System	Management	H	Git	2	10	64	36.29
005	QOI Format Codec	Algorithm	E	C++	2	10	512	58.87
006	Minesweeper-2025 Assignment	Game	E	C++	2	30	256	53.51
007	BASIC Interpreter Assignment	Interpreter	E	Git	1	5	256	47.67
008	mov Language Problems	Assembly	E	mov	8	-	-	54.70
009	STLVector Vector	Data Structure	E	C++	1	100	768	58.46
010	STLList List (Doubly-Linked List)	Data Structure	E	C++	1	25	768	30.76
011	STLPriority Priority Queue	Data Structure	E	C++	1	15	512	57.25
012	STLMap LinkedHashMap	Data Structure	E	C++	1	24	893	43.36
013	STLMap Map	Data Structure	E	C++	2	30	893	58.21
014	Python Interpreter Assignment	Interpreter	E	Git	1	16	512	46.23
015	File Storage	Storage	H	Git	1	16	6	42.71
016	File Storage BPT	Storage	H	Git	1	5	64	40.11
017	Train Ticket Management System	Management	H	Git	1	40	47	53.24
018	Scheme Interpreter	Interpreter	E	Git	1	1.5	244	32.94
019	Mini-Aidiv-N: GPU Memory Optimization	Optimization	E	C++	1	1	244	36.89
020	Buddy Algorithm	Optimization	E	Git	1	10	244	33.33

## B. Interaction Performance Details

Table 6 reports per-problem interaction-level statistics aggregated over execution logs from the Claude Code agent framework across all evaluated models. The table summarizes final scores, agent–environment interaction measures (token usage and interaction turns), and human submission scale statistics (average lines of code and number of files).

Table 6. Per-problem final scores, aggregated agent–environment interaction statistics in Claude Code, and human submission scale.

Problem	Final Score	Tokens (M)	Turns	Avg. Lines	Files
001	98.80	0.42	42.6	9.8	1
002	42.65	7.33	173.2	547.7	1
003	18.27	4.87	144.4	475.3	1
004	34.04	3.81	135.8	1659.0	18
005	77.40	2.09	107.0	101.5	1
006	81.67	4.86	149.8	111.3	1
007	77.44	6.75	205.0	750.5	17
008	29.01	4.96	189.6	42.1	1
009	93.26	2.50	85.4	129.9	1
010	76.08	3.23	118.0	180.0	1
011	99.07	2.18	85.6	77.0	1
012	69.60	5.66	148.4	298.6	1
013	54.67	3.94	123.8	376.4	1
014	9.20	6.83	161.4	2377.0	17
015	79.11	3.07	131.4	2093.9	3
016	97.87	1.05	65.2	3139.4	11
017	23.27	6.53	153.0	4204.3	20
018	20.36	13.31	262.2	691.8	13
019	33.27	5.31	130.2	157.2	1
020	34.00	7.52	150.4	111.3	4

## C. Scoring Formula

### C.1. Execution Score

For each problem, the Online Judge evaluates submissions against a test suite consisting of  $N$  test cases. The standard scoring method assigns a weight  $w_i$  to each test case  $i$  based on its complexity or importance. The raw execution score is computed as:

$$S_{\text{raw}} = \sum_{i=1}^N w_i \cdot \mathbf{1}[\text{test case } i \text{ passed}]$$

where  $\mathbf{1}[\cdot]$  is the indicator function. The raw score is then linearly normalized to a 0–100 scale:

$$S_{\text{exec}} = \frac{S_{\text{raw}}}{\sum_{i=1}^N w_i} \times 100$$

Note that different problems may adopt alternative scoring schemes depending on their specific evaluation requirements. For example, some problems may use uniform weights across all test cases, while others may assign higher weights to advanced test cases or apply penalty-based scoring for partial correctness. Our evaluation scripts automatically handle these problem-specific scoring variations and normalize all scores to a consistent 0–100 scale for fair comparison across problems.

### C.2. Code Review Score

The code review score  $S_{\text{cr}}$  is computed based on a set of problem-specific rules, combining rule-based checks and LLM-based qualitative assessments. Each rule contributes to the final code review score, which is also normalized to a 0–100 scale. Detailed rule definitions are provided in Section D.

### C.3. Final Score

The final score for each submission is a weighted combination of the execution score and the code review score:

$$S_{\text{final}} = 0.8 \times S_{\text{exec}} + 0.2 \times S_{\text{cr}}$$

This weighting prioritizes functional correctness (80%) while ensuring compliance with specification-level requirements (20%).

For problems associated with multiple OJ problem IDs, the execution score is computed as a weighted average of normalized scores across all associated problems:

$$S_{\text{exec}} = \sum_{j=1}^M \alpha_j \cdot S_{\text{exec}}^{(j)}$$

where  $M$  is the number of associated OJ problems,  $S_{\text{exec}}^{(j)}$  is the normalized execution score for the  $j$ -th OJ problem, and  $\alpha_j$  is the corresponding weight satisfying  $\sum_{j=1}^M \alpha_j = 1$ . The specific weights for each problem are documented in the respective task descriptions provided to agents.

When multiple submissions are allowed, the final reported score for each agent-problem pair is the *maximum* final score achieved across all valid submissions within the submission limit.

## D. Code Review Evaluation Rules

ProjDevBench employs a comprehensive code review system combining rule-based Python scripts for automatic verification and LLM-based evaluation for qualitative assessment. The complete rule definitions are stored in `scripts/cr/[problem_id]/cr.list.json` files for each problem.

### D.1. Check Function Registry

The code review framework (`scripts/cr/common/checks.py`) provides the following automated check functions:

Table 7. Available check functions in the code review framework (`checks.py`).

Function	Description
<code>ensure_gitignore_contains</code>	Verify <code>.gitignore</code> contains required entries (e.g., <code>CMakeFiles/</code> , <code>CMakeCache.txt</code> )
<code>forbid_pattern_in_files</code>	Forbid specific pattern in specified files
<code>forbid_pattern_recursive</code>	Forbid pattern across entire repository with optional suffix filtering and comment stripping
<code>ensure_allowed_includes</code>	Restrict standard library header usage to allowed list
<code>ensure_files_exist</code>	Ensure required files exist in submission
<code>ensure_files_unchanged</code>	Verify template files remain unchanged from reference
<code>ensure_cmake_outputs_code</code>	Check <code>CMakeLists.txt</code> produces executable named “code”
<code>llm_as_a_judge</code>	LLM-based qualitative evaluation for code quality and specification compliance

## D.2. Problem-Specific Code Review Rules

Table 8 and Table 9 summarizes the complete set of problem-specific code review rules used in our benchmark.

## E. Evaluation Infrastructure

### E.1. Docker Base Image Configuration

ProjDevBench uses a custom Docker image based on Ubuntu 24.04 with the following components:

```
Docker Base Image (Dockerfile)

FROM ubuntu:24.04
ENV DEBIAN_FRONTEND=noninteractive

# Install Node.js 20
RUN apt-get update && apt-get install -y curl \
    && curl -fsSL https://deb.nodesource.com/setup_20.x | bash - \
    && apt-get install -y nodejs

# Install toolchain and Python
RUN apt-get update && apt-get install -y \
    gcc-13 g++-13 cmake \
    python3.12 python3.12-dev python3-pip \
    iverilog git curl jq build-essential sudo \
    && ln -sf /usr/bin/gcc-13 /usr/bin/gcc \
    && ln -sf /usr/bin/g++-13 /usr/bin/g++ \
    && ln -sf /usr/bin/python3.12 /usr/bin/python3

# Install Python dependencies
RUN python3 -m pip install requests --break-system-packages

# Install GitHub CLI
RUN curl -fsSL https://cli.github.com/packages/githubcli-archive-keyring.gpg \
    | dd of=/usr/share/keyrings/githubcli-archive-keyring.gpg \
    && apt-get update && apt-get install gh -y

# Install AI Coding Agents
RUN npm install -g @google/gemini-cli
```

```
RUN npm install -g @anthropic-ai/claude-code
RUN npm install -g @github/copilot
RUN npm install -g @vibe-kit/grok-cli
RUN npm install -g @openai/codex
RUN npm install -g @augmentcode/augie
```

## **E.2. Evaluation Pipeline**

The evaluation pipeline is orchestrated by `scripts/run_evaluation.sh`, which performs the following steps:

1. **Configuration Loading:** Read problem configuration from `config/problem_registry.json` to obtain maximum submission limits and other parameters.
2. **Environment Validation:** Verify required API tokens (GITHUB\_TOKEN, OJ\_TOKEN) and agent-specific credentials.
3. **Docker Container Initialization:** Launch isolated container with:
  - Problem files mounted read-only at `/problems/[problem_id]`
  - Test data mounted read-only at `/data_READONLY/[problem_id]`
  - Evaluation scripts mounted at `/scripts`
  - Writable log directory at `/workspace/logs`
4. **Workspace Setup** (`run_agent_base.sh`):
  - Copy problem files to writable workspace `/workspace/problem_[id]`
  - Initialize Git repository with `git init`
  - Create remote GitHub repository using `gh repo create`
  - Configure token-based authentication for Git operations
5. **Agent Execution:** Run agent-specific script (e.g., `run_claude_code.sh`) with standardized prompt
6. **Result Collection:** Capture submission IDs and copy logs to host
7. **OJ Submission:** Agent autonomously submits to OJ via `oj_client.py`
8. **Code Review:** Execute problem-specific checks from `cr_list.json`

## **E.3. Resource Limits**

Our containerized evaluation environment enforces the following resource limits: memory is capped at 8 GB (configurable via `AGENT_MEMORY_LIMIT`), CPU is limited to 4 cores (configurable via `AGENT_CPU_LIMIT`), and the Node.js heap is set to 6 GB (`--max-old-space-size=6144`). Containers have full internet access for network operations.

## **F. Agent Prompts**

### **F.1. Single Problem Prompt**

The following prompt is used for problems with a single OJ problem ID:

#### **Single Problem Evaluation Prompt**

You are a professional programming expert and Git expert. You are now in a Git repository and need to complete the following tasks:

#### **Current Environment**

- Repository URL: <https://github.com/{user}/{repo}>

- Working Directory: /workspace/problem\_{id}
- OJ Bench Problem ID: {problem\_id}
- OJ Problem ID: {o\_j\_id}
- Maximum Submission Limit: {max\_submissions} attempts

#### **Important Scoring Rules**

- Final score is based on the **highest score among all valid submissions**
- Submissions exceeding limit will not be counted and incur penalties
- Each test point may have different score weights

#### **Your Tasks**

1. **Analyze:** Read README.md and understand requirements
2. **Develop:** Implement the optimal solution
3. **Git Management:** Commit and push changes; verify push success
4. **Submit to OJ:** Use obj-client.py for submission
5. **Iterate:** Analyze errors and optimize within submission limit
6. **Record:** Document changes with clear commit messages

#### **Important Reminders**

- Compile and test locally before submission
- If submission stuck pending, abort (doesn't count) and resubmit
- Full control over workspace including file modifications

## **F.2. Multiple Problems Prompt**

For problems with multiple OJ problem IDs sharing submission limits:

### **Multiple Problems Evaluation Prompt (Key Differences)**

#### **Additional Environment**

- OJ Problem IDs: {id1, id2, ...} (comma-separated)
- Maximum Submission Limit: {max} attempts **SHARED across all problems**

#### **Key Differences**

- Submission limit is **SHARED** across all problem IDs
- When submitting, specify which problem ID to submit to
- Track remaining attempts across all problems
- Plan submissions wisely to maximize overall score

## **G. Detailed Error Examples**

### **Example 1: CMake Configuration Error (Problem 017)**

```
CMake Error at CMakeLists.txt:15:  
add_executable called with incorrect arguments
```

Configuration failed.

**Root Cause:** Agent generated CMakeLists.txt with incorrect source file paths.

**Example 2: Logic Error (Problem 003 - ICPC System)**

Test: basic\_4  
Expected: Team A ranked 1st  
Actual: Team B ranked 1st

Reason: Incorrect tie-breaking logic in penalty time calculation.

**Example 3: Memory Limit Exceeded (Problem 015)**

Test: pressure\_1  
Status: Memory Limit Exceeded  
Used: 8.2 MiB / Limit: 6 MiB

Reason: Agent allocated in-memory hash table instead of disk-based B+ tree.

**Example 4: Runtime Error (Problem 018 - Scheme)**

Test: closure\_test  
Status: Runtime Error (SIGSEGV)

Reason: Stack overflow in recursive closure evaluation without proper tail-call optimization.

## H. Statistical Analysis

**Performance Distribution:**

- Mean score: 54.16 (std: 32.4)
- Median score: 55.0
- Problems with >80% pass rate: 7 (35%)
- Problems with <20% pass rate: 5 (25%)

**Correlation Analysis:**

- Problem complexity vs. score:  $r = -0.72$  (strong negative)
- Submission count vs. final score:  $r = 0.15$  (weak positive)
- Code review score vs. OJ score:  $r = 0.68$  (moderate positive)

**Statistical Significance:** Pairwise comparison of top agents (Cursor vs. Claude Code) shows statistically significant difference ( $p < 0.05$ , paired t-test) in average performance.

Table 8. Complete code review rules for all problems (Part I).

ID	Rule Name	Check Type	Description
001	CMake Artifact Ignore Project Readability	gitignore_entries llm_as_a_judge	.gitignore must list CMakeFiles/ and CMakeCache.txt Assess overall project readability and organization
002	Forbid using namespace std Ensure code.cpp Exists Code Readability	forbid_pattern_recursive require_files llm_as_a_judge	No “using namespace std;” in sources/headers Submission requires code.cpp file Assess code.cpp readability
003	Forbid CMake Artifacts CMakeLists Outputs code Project Readability	forbid_pattern_recursive cmakelists_outputs_code llm_as_a_judge	Repository must not contain CMake build files CMakeLists.txt must produce “code” executable Assess overall project readability
004	Forbid CMake Artifacts CMakeLists Outputs code Disallow Persistent Main Data Forbid Filesystem-as-Database Project Readability	forbid_pattern_recursive cmakelists_outputs_code llm_as_a_judge llm_as_a_judge llm_as_a_judge	Repository must not contain CMake build files CMakeLists.txt must produce “code” executable Check avoiding keeping data permanently in memory Check no filesystem-as-database style design Assess overall project readability
005	Restrict Modifications qoi.h Readability	require_unmodified llm_as_a_judge	Only edit qoi.h; other files must match template Assess qoi.h readability
006	Restrict Modifications server.h/client.h Readability	require_unmodified llm_as_a_judge	Do not modify basic.cpp or advanced.cpp Assess server.h and client.h readability
007	CMakeLists Outputs code Keep Basic/Utils Templates Project Readability	cmakelists_outputs_code require_unmodified llm_as_a_judge	CMakeLists.txt must produce “code” executable Basic/Utils helper files must match template Assess overall project readability
008	Line Limit and Bounds .mv Files Readability	llm_as_a_judge llm_as_a_judge	Code length $\leq$ 65,536 lines; no out-of-bounds access Assess .mv files readability
009	Restrict Standard Headers Keep Helper Headers vector.hpp Readability	allowed_includes require_unmodified llm_as_a_judge	Only allow cstdio, cstring, iostream, cmath, string exceptions.hpp and utility.hpp must match template Assess vector.hpp readability
010	Restrict Standard Headers Keep Helper Headers list.hpp Readability	allowed_includes require_unmodified llm_as_a_judge	Only allow cstdio, cstring, iostream, cmath, string exceptions.hpp and utility.hpp must match template Assess list.hpp readability
011	Restrict Standard Headers Keep Helper Headers priority_queue.hpp Readability	allowed_includes require_unmodified llm_as_a_judge	Only allow cstddef, functional (from template) exceptions.hpp and utility.hpp must match template Assess priority_queue.hpp readability
012	Restrict Standard Headers Keep Helper Headers linked_hashmap.hpp Readability	allowed_includes require_unmodified llm_as_a_judge	Only allow cstdio, cstring, iostream, cmath, string exceptions.hpp and utility.hpp must match template Assess linked_hashmap.hpp readability
013	Restrict Standard Headers Keep Local Test Helpers map.hpp Readability	allowed_includes require_unmodified llm_as_a_judge	Only allow cstdio, cstring, iostream, cmath, string exceptions.hpp and utility.hpp must match template Assess map.hpp readability
014	CMake Artifact Ignore Project Readability	gitignore_entries llm_as_a_judge	.gitignore must list CMakeFiles/ and CMakeCache.txt Assess overall project readability
015	Forbid CMake Artifacts CMakeLists Outputs code Project Readability	forbid_pattern_recursive cmakelists_outputs_code llm_as_a_judge	Repository must not contain CMake build files CMakeLists.txt must produce “code” executable Assess overall project readability
016	Forbid CMake Artifacts CMakeLists Outputs code Project Readability	forbid_pattern_recursive cmakelists_outputs_code llm_as_a_judge	Repository must not contain CMake build files CMakeLists.txt must produce “code” executable Assess overall project readability
017	Forbid CMake Artifacts CMakeLists Outputs code Restrict STL and Algorithm Project Readability	forbid_pattern_recursive cmakelists_outputs_code forbid_pattern_recursive llm_as_a_judge	Repository must not contain CMake build files CMakeLists.txt must produce “code” executable No STL containers (except std::string); no <algorithm> Assess overall project readability

*Table 9.* Complete code review rules for all problems (Part II).

ID	Rule Name	Check Type	Description
018	Forbid CMake Artifacts Project Readability	forbid_pattern_recursive llm_as_a_judge	Repository must not contain CMake build files Assess overall project readability
019	GPU Simulator API Usage GPU Instruction Constraints src.hpp Readability	llm_as_a_judge llm_as_a_judge llm_as_a_judge	Verify correct GPU simulator API and memory allocation No stdout logging; no direct Matrix writes Assess src.hpp readability
020	Forbid CMake Artifacts Project Readability	forbid_pattern_recursive llm_as_a_judge	Repository must not contain CMake build files Assess overall project readability