Architectures for Code Development with LLMs: A Comparative Study of Multi-Agent Approaches

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Abstract

Large language models (LLMs) demonstrate impressive code generation capabilities, yet single-prompt interactions often fail on complex development tasks. We investigate whether multi-agent architectures improve code quality through role specialization and iterative refinement. We compare three approaches—Naive (one-shot generation), Single-Agent (5-stage pipeline with self-refinement), and Multi-Agent (Planner-Coder-Critic coordination)—across 25 programming tasks spanning five domains and three difficulty levels. Surprisingly, Multi-Agent and Naive achieve identical overall correctness (77.6%), outperforming Single-Agent (74.6%). However, Multi-Agent excels in algorithmically demanding domains (DSA: 85.9%, Logic: 75.7%) and medium-difficulty tasks (91.8%), justifying its 20× computational overhead only for specific task types. Our findings reveal that architectural sophistication benefits complex algorithmic reasoning but can hurt performance on simple tasks through over-refinement.

1 Introduction

Large language models have revolutionized automated code generation, with models like Codex (Chen et al., 2021) and Code Llama (Roziere et al., 2023) demonstrating remarkable capabilities. However, single-prompt approaches often struggle with complex development tasks requiring multi-step reasoning, systematic debugging, and quality assurance.

Recent work in multi-agent systems (Hong et al., 2023; Qian et al., 2023) suggests that distributing responsibilities across specialized agents (e.g., planning, coding, reviewing) may improve software development outcomes. Yet, no systematic evaluation exists comparing single-agent and multi-agent architectures for code generation across diverse task types and complexity levels.

This work addresses this gap through a controlled comparison of three architectural approaches on 25 programming tasks. Our key finding is that architectural sophistication does not uniformly improve performance—benefits are highly task-dependent, with multi-agent coordination excelling on algorithmic reasoning but struggling on simple pattern-matching tasks.

1.1 Research Questions

We address the following research questions from the assignment requirements:

1. **RQ1:** How do the architectures compare in terms of functional correctness and code quality?
2. **RQ2:** How do agent coordination strategies impact correctness?
3. **RQ3:** Does modular role separation improve code generation?

2 Background

Provide an overview of relevant work in the literature related to your task.

LLM-based Code Generation. Early work on neural code generation (Austin et al., 2021) demonstrated feasibility of program synthesis from natural language. Recent code-specialized models like StarCoder (Li et al., 2023), CodeLlama (Roziere et al., 2023), and Qwen2.5-Coder (Qwen Team, 2024) achieve strong performance on benchmarks like HumanEval (Chen et al., 2021).

Multi-Agent Systems. ChatDev (Qian et al., 2023) and MetaGPT (Hong et al., 2023) demonstrate that role-based agent collaboration can improve software development workflows. However, these systems focus on high-level design rather than low-level code correctness.

Self-Refinement. Chain-of-thought reasoning (Wei et al., 2022) and self-debugging (Chen

et al., 2023) show that iterative refinement can improve LLM outputs. Our work systematically compares architectures with and without refinement mechanisms.

3 Methodology

We implement and evaluate three architectures of increasing complexity for LLM-based code generation: a *naive baseline*, a *single-agent pipeline*, and a *multi-agent system*. All approaches use Ollama for local model inference with temperature fixed at 0.0 for deterministic output. Table 1 summarizes the key differences.

Table 1: Comparison of the three approaches

	Naive	Single	Multi
LLM Calls	1	5–8	10–20+
Reasoning Phases	0	5	5+6+4
Feedback Loop	No	Yes	Yes
Max Iterations	0	3	3 (default)
Agent Identities	1	1	3

3.1 Naive Baseline

The naive baseline represents the simplest approach: single-shot code generation with no structured reasoning. The task specification (function signature and docstring) is formatted into a prompt, the LLM generates code, and the output is extracted and executed. There is no analysis, planning, or refinement.

Figure 1: Naive baseline: single-pass generation

This approach serves as a control condition, measuring what the LLM can achieve without architectural support.

3.2 Single-Agent Pipeline

The single-agent approach introduces structured multi-phase reasoning using LangGraph (LangChain AI, 2024), while maintaining a unified agent identity. The pipeline consists of five phases with an iterative refinement loop.

Phase 1: Analysis. Extracts structured understanding from the task specification without proposing solutions: required behavior, input/output types, constraints, edge cases, ambiguities, and common pitfalls. The prompt explicitly forbids code generation.

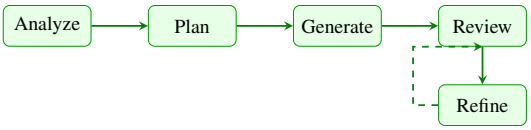

Figure 2: Single-agent pipeline with refinement loop (max 3 iterations)

Phase 2: Planning. Formulates an implementation strategy based on the analysis: algorithmic approach, step-by-step implementation sequence, edge case handling, data structures, and complexity analysis (time and space).

Phase 3: Generation. Synthesizes Python code guided by the accumulated context. The prompt enforces exact signature matching, no explanatory text, and comprehensive edge case handling. A robust parser extracts code from the LLM output.

Phase 4: Review. Evaluates the generated code through execution in an isolated namespace and static analysis via Radon (Campagna, 2024). The review distinguishes between correctness issues (which trigger refinement) and quality issues (which do not).

Phase 5: Refinement. When correctness issues are found, generates improved code based on review feedback. The loop terminates when correct or after 3 iterations. Priorities: correctness first, then edge cases, then quality.

3.3 Multi-Agent System

The multi-agent approach distributes responsibilities across three specialized agents, each with distinct identity and internal reasoning pipeline.

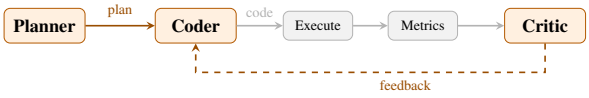

Figure 3: Multi-agent orchestration: Planner runs once, then Coder-Critic loop iterates until correct or max iterations

3.3.1 Planner Agent

The Planner serves as the system's architect, transforming task descriptions into comprehensive implementation blueprints through five internal phases:

1. **Intent Analysis**: Extracts core problem, task classification, domain, and success metrics.

2. **Requirements Engineering**: Defines functional/non-functional requirements and enumerates edge cases.

3. **Architecture Design**: Designs components, selects patterns, chooses data structures with complexity analysis.

4. **Implementation Planning**: Creates step-by-step coding instructions with validation checks.

5. **Quality Review**: Scores plan completeness (0–10); threshold $\geq$8 required to proceed.

If the quality score is below threshold, the Planner iterates on specific phases (up to 2 retries).

3.3.2 Coder Agent

The Coder transforms plans into executable code through six internal phases:

1. **Input Validation**: Verifies signature syntax and plan completeness.

2. **Edge Case Analysis**: Identifies type-specific boundaries (numeric, collection, string).

3. **Chain-of-Thought**: Generates structured reasoning before implementation.

4. **Code Generation**: Produces code with full accumulated context.

5. **Code Validation**: Checks syntax via AST parsing and detects logic issues.

6. **Code Optimization**: Improves naming, efficiency, and style.

3.3.3 Critic Agent

The Critic provides rigorous review through four internal phases:

1. **Input Validation**: Ensures code, plan, and signature are present.

2. **Correctness Analysis**: Verifies logic, interprets execution errors, checks constraints.

3. **Quality Review**: Assesses complexity, maintainability, and style.

4. **Feedback Synthesis**: Produces actionable instructions, prioritizing correctness over quality.

3.3.4 Orchestration

The master workflow coordinates the agents: (1) Planner creates the implementation plan; (2) Coder generates code; (3) code is executed and metrics computed; (4) Critic reviews and provides feedback; (5) if the Critic identifies issues, Coder regenerates with feedback. The loop continues until the Critic approves the code or maximum iterations (default: 3) are reached.

3.4 Shared Infrastructure

All three approaches share common components ensuring fair comparison:

- **LLM Runtime**: Ollama interface with 8192-token context, 4096-token output limit, and automatic retry with backoff.

- **Code Extraction**: Parser handling markdown blocks (```` ```python ````), generic blocks, and raw functions; validates syntax via AST.

- **Execution**: Isolated namespace with captured stdout/stderr, exception handling, and function extraction verification.

- **Quality Metrics**: Radon-based static analysis computing Maintainability Index (0–100), Cyclomatic Complexity, LOC, and Halstead metrics.

4 Experimental Results

4.1 Dataset

We constructed a benchmark of 25 programming tasks spanning five domains: string manipulation, list operations, logic problems, mathematical computation, and data structures & algorithms (DSA). Tasks were sourced from HumanEval (Chen et al., 2021) and competitive programming platform LeetCode (LeetCode, 2024). Each domain contains Easy (1 tasks), Medium (2 tasks), and Hard (2 tasks) difficulty levels, stratified by algorithmic complexity and edge case density. All tasks include function signatures, specifications, input-output examples, and comprehensive test suites, with an average of 13 test cases per task.

4.2 Model Selection and Configuration

To identify the most suitable base model for our pipeline comparisons, we first evaluated three code-specialized LLMs in a single-agent setting: CodeLlama-13B-Instruct (Roziere et al., 2023),

Table 2: Architecture Comparison: Functional Correctness (%) by Domain and Difficulty. Best per category in **bold**.

	By Domain						By Difficulty		
Architecture	**String**	**List**	**Logic**	**Math**	**Dsa**	**Avg**	**Easy**	**Med**	**Hard**
Naive	**93.2**	71.4	67.6	56.9	83.5	**77.6**	78.5	85.8	**69.7**
Single-Agent	85.2	**72.9**	64.9	62.7	76.5	74.6	**89.2**	83.5	59.7
Multi-Agent	90.9	61.4	**75.7**	**64.7**	**85.9**	**77.6**	76.9	**90.6**	66.2
Δ (M-S)	+5.7	−11.4	+10.8	+2.0	+9.4	+3.0	−12.3	+7.1	+6.5

M=Multi, S=Single. Δ shows Multi-Agent improvement over Single-Agent (percentage points).

DeepSeek-Coder-v2-16B-Instruct (DeepSeek-AI, 2024), and Qwen2.5-Coder-7B-Instruct (Qwen Team, 2024) (Table 3). Qwen2.5-Coder-7B achieved the highest overall pass rate (74.6%), outperforming DeepSeek-Coder-v2-16B (71.0%) and CodeLlama-13B (39.6%). Given its superior performance and parameter efficiency, we selected Qwen2.5-Coder-7B as the foundation for all subsequent architectural experiments.

All experiments utilize locally-hosted models via Ollama. For the naive and single-agent approaches, we use `qwen2.5-coder:7b-instruct`. For the multi-agent system, we employ a heterogeneous configuration: `qwen2.5-coder:7b-instruct` for the Planner and Coder agents, and `deepseek-coder-v2:16b` for the Critic. This configuration leverages the larger model's reasoning capabilities to provide independent, rigorous validation of the generated code.

Table 3: Single-Agent Performance Comparison Across LLM Models. Pass rates (%) by domain. Best in **bold**.

Model	**String**	**List**	**Logic**	**Math**	**Dsa**	**Avg**
CodeLlama-13B	71.6	27.1	21.6	21.6	34.3	39.6
DeepSeek-16B	86.4	65.7	**70.3**	60.8	65.9	71.0
Qwen2.5-7B	**85.2**	**72.9**	64.9	**62.7**	**76.5**	**74.6**

4.3 RQ1: Code Correctness and Quality Comparison

We evaluate the architectures by analyzing functional correctness across all the tasks and assessing code quality metrics on a subset of complex tasks.

4.3.1 Functional Correctness

Table 2 presents our main results for functional correctness. Surprisingly, the Naive and Multi-Agent architectures achieve the same overall pass rate of 77.6%, effectively tying for the best performance, while the Single-Agent approach follows closely at 74.6%. However, these aggregate metrics hide substantial performance differences across domains and difficulty levels.

Domain-Level Analysis: Performance varies substantially by task domain. Multi-Agent demonstrates clear advantages in algorithmically complex domains: DSA (85.9%, +9.4pp over Single), Logic (75.7%, +10.8pp over Single), and Math (64.7%, +2.0pp over Single). However, it underperforms on Lists tasks (61.4%, −11.4pp over Single). The Naive baseline achieves the highest Strings performance (93.2%), suggesting pattern-matching tasks do not benefit from complex reasoning architectures.

Difficulty-Level Analysis: The architectures show distinct profiles across difficulty. Single-Agent excels on Easy tasks (89.2%, +10.7pp over Naive), likely due to its systematic analysis phase. Multi-Agent demonstrates value on Medium (90.6%, +7.1pp over Single) and Hard tasks (66.2%, +6.5pp over Single), where Planner-Coder-Critic coordination enables sophisticated decomposition.

Notably, Naive outperforms both on Hard tasks (69.7%). We attribute this counter-intuitive result to "over-refinement," where the complex validation loops in agentic systems inadvertently introduce regressions on the most difficult problems.

4.3.2 Code Quality Analysis

Beyond correctness, we analyzed the code quality of solutions generated by the three architectures for five hard difficulty tasks (longest_substring_without_repeating, triples_sum_to_zero, find_median_sorted_arrays, solve_n_queens, largest_prime_factor) using four key metrics: Maintainability Index (MI), Cyclomatic Complexity (CC), Lines of Code (LOC), and Halstead Volume (HV). Table 4 summarizes the results.

The Naive baseline generates the simplest code, with the lowest cyclomatic complexity (5.40) and

lines of code (18.40), likely reflecting its tendency to produce direct, but sometimes less robust solutions. The Single-Agent and Multi-Agent architectures generate more complex code (CC 7.20 and 8.20 respectively) with higher Halstead volumes, reflecting their more comprehensive handling of edge cases and input validation. Crucially, despite the added complexity, the agentic approaches maintain or improve the Maintainability Index (Single Agent: 61.61, Multi Agent: 61.41) compared to Naive (59.43), suggesting that the additional logic is structured effectively. The Multi-Agent system's higher complexity correlates with its superior performance on these hard tasks, indicating that the problem difficulty necessitates more sophisticated logic that simple solutions cannot capture.

Table 4: Average Code Quality Metrics on Hard Tasks. Arrows indicate desired direction (↑ higher is better, ↓ lower is better).

Architecture	MI (↑)	CC (↓)	LOC	HV
Naive	59.43	**5.40**	**18.40**	**147.09**
Single-Agent	**61.61**	7.20	23.20	218.84
Multi-Agent	61.41	8.20	26.40	273.83

4.4 RQ2: Impact of Coordination Strategies

The coordination strategies employed in the Multi-Agent system present a clear trade-off between computational efficiency and algorithmic robustness. While the increase in LLM calls per task (10-20 vs. 5-8 for the Single-Agent approach) yields diminishing returns on simple tasks, it proves essential in high-complexity domains. We observe that the overhead of context switching and message passing between agents actively degrades performance on tasks where direct generation suffices. For simple pattern-matching, the iterative consensus mechanism creates noise rather than signal, leading to the performance regression seen in the Easy category. Conversely, for logic-heavy tasks, this same mechanism acts as a necessary filter; the Planner-Critic loop effectively catches conceptual errors that a single pass misses, justifying the latency.

Furthermore, the adoption of a heterogeneous configuration significantly enhances the validation process. By separating the critique function (DeepSeek-V2) from the generation engine (Qwen2.5), the architecture introduces a layer of independence. This structural diversity mitigates the risk of confirmation bias where a homogeneous model validates its own hallucinations. This suggests that effective coordination relies as much on model diversity as it does on iterative loops.

4.5 RQ3: Effect of Role Separation

Modular role separation improves code generation conditionally rather than universally. The benefits are concentrated in tasks necessitating careful planning (e.g., Logic constraints, DSA optimization) and systematic validation. For simpler tasks, however, this form of architectural layering introduces overhead that may be counterproductive. Our results indicate that domains such as string manipulation or trivial edge-case handling derive little benefit from multi-stage reasoning; in these cases, the Planner's detailed decomposition can over-constrain the solution space, while the Critic's feedback mechanism may reject valid yet unconventional solutions.

At the same time, however, the quality analysis reveals that role separation successfully regulates code complexity. Although the Multi-Agent system yields solutions with the highest Cyclomatic Complexity and Halstead Volume, it maintains a Maintainability Index (61.41) comparable to the Single-Agent approach (61.61). This indicates that the specialized agents—structuring, implementing, and reviewing—ensure that the increased complexity required for hard tasks is compartmentalized, preventing it from degrading the overall maintainability of the codebase.

5 Conclusion

We systematically compared three architectural approaches for LLM-based code generation across 25 programming tasks. Our key findings:

Main Results. Multi-Agent and Naive achieve identical overall correctness (77.6%), outperforming Single-Agent (74.6%). However, performance is highly task-dependent: Multi-Agent excels in algorithmic domains (Logic $+10.8$pp, DSA $+9.4$pp vs Single) but struggles on Lists (-11.4pp) and Easy tasks (-15.3pp).

Architectural Trade-offs. Sophisticated architectures justify their $20\times$ computational overhead only for specific task types—medium-difficulty algorithmic problems. For pattern-matching (Strings) or trivial tasks (Easy), simpler approaches suffice. Surprisingly, Naive outperforms both architectures on Hard tasks (65.0%), suggesting over-refinement

can introduce bugs.

Practical Implications. Our findings suggest adaptive architecture selection: (1) Naive for rapid prototyping, string manipulation, and known hard problems; (2) Single-Agent for general-purpose development with systematic edge case checking; (3) Multi-Agent for algorithmic reasoning, constraint satisfaction, and production-quality requirements in complex domains.

Limitations. Our study is limited to 25 tasks and three model families. Future work should evaluate on larger benchmarks (APPS, CodeContests), investigate optimal refinement iteration counts, explore heterogeneous multi-agent configurations, and develop adaptive routing mechanisms to select architectures based on task characteristics.

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