

A Comparative Analysis of Multi-Agent Frameworks for Automated Software Bug Resolution

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Abstract—Large Language Models (LLMs) have significantly transformed software engineering by enabling intelligent code generation, automated testing, documentation, and defect localization. While single-agent systems have demonstrated promising performance in software maintenance, they often struggle with complex debugging tasks requiring iterative reasoning, collaborative verification, and long execution workflows. Recent advances in multi-agent orchestration frameworks enable multiple specialized agents to cooperate during software debugging, thereby improving reasoning quality, modularity, and maintainability.

This paper presents a comparative analysis of five representative multi-agent frameworks—LangGraph, Microsoft AutoGen, CrewAI, OpenAI Agents SDK, and SmolAgents—for automated software bug resolution. A generalized seven-agent debugging architecture is proposed to provide a framework-independent evaluation methodology. The study examines architectural design, workflow orchestration, execution efficiency, scalability, collaboration mechanisms, token utilization, maintainability, and deployment complexity. Mathematical formulations describing collaborative debugging workflows are introduced together with evaluation metrics suitable for benchmarking autonomous software maintenance systems. Experimental methodology based on publicly available software engineering benchmarks is described, and comparative performance trends are discussed. The proposed framework provides researchers and practitioners with a reproducible methodology for evaluating collaborative AI systems designed for intelligent software maintenance while identifying architectural trade-offs among modern multi-agent frameworks.

Index Terms—Large Language Models, Multi-Agent Systems, Software Engineering, Automated Program Repair, LangGraph, AutoGen, CrewAI, OpenAI Agents SDK

I. INTRODUCTION

Software maintenance accounts for a substantial proportion of software development cost, with debugging and defect correction representing one of its most resource-intensive activities. As modern software systems continue to increase in complexity through cloud-native architectures, microservices, distributed computing, and continuous integration pipelines, identifying and repairing defects has become increasingly challenging.

Recent advances in Large Language Models (LLMs) have introduced new possibilities for automating software engineering tasks. Contemporary code-oriented language models are

capable of understanding source code semantics, generating implementations, producing documentation, constructing unit tests, and repairing software defects. These capabilities have enabled AI-assisted programming environments that substantially improve developer productivity.

Despite these advances, most existing debugging assistants rely on a single reasoning agent responsible for understanding the software context, identifying faults, generating candidate repairs, validating modifications, and explaining outcomes. Such monolithic reasoning frequently suffers from context limitations, hallucinated repairs, inconsistent multi-step reasoning, and insufficient verification.

Multi-agent architectures address these shortcomings by distributing debugging responsibilities across specialized intelligent agents. Rather than depending upon a single reasoning process, collaborative agents independently perform bug localization, semantic analysis, root cause identification, repair generation, validation, testing, and code review. Intermediate outputs are exchanged between agents, allowing iterative refinement before accepting a software patch.

Several orchestration frameworks have recently emerged to simplify the construction of collaborative AI systems. LangGraph emphasizes graph-based execution with explicit workflow control. Microsoft AutoGen enables conversational collaboration among autonomous agents. CrewAI introduces role-based teamwork inspired by human development organizations. OpenAI Agents SDK provides production-oriented orchestration using structured handoffs and integrated tools. SmolAgents focuses on lightweight execution with minimal computational overhead.

Although these frameworks have gained considerable popularity, systematic comparisons focusing specifically on automated software debugging remain limited. Existing evaluations frequently investigate individual frameworks independently, making objective comparison difficult because of inconsistent datasets, evaluation metrics, and experimental procedures.

This paper proposes a unified benchmarking methodology based on a generalized collaborative debugging architecture that enables reproducible comparison across multiple orches-

tration frameworks. The proposed methodology evaluates architectural flexibility, debugging effectiveness, execution efficiency, scalability, computational cost, maintainability, and deployment complexity under identical experimental conditions.

The primary contributions of this paper are:

- A generalized multi-agent architecture for automated software debugging.
- A framework-independent benchmarking methodology.
- Comparative analysis of five modern orchestration frameworks.
- Mathematical formulation of collaborative debugging workflows.
- Discussion of research challenges and future opportunities in autonomous software engineering.

II. RELATED WORK

A. AI-Assisted Software Engineering

Machine learning has progressively transformed software engineering by supporting code completion, defect prediction, automated testing, and software maintenance. Transformer-based language models trained on large software repositories have demonstrated remarkable capabilities in understanding programming languages and generating executable source code.

Models such as GPT-series, Code Llama, StarCoder, and DeepSeek-Coder have enabled intelligent software assistants capable of producing syntactically correct implementations while explaining program behavior using natural language. Recent benchmarking efforts such as SWE-bench and HumanEval further illustrate the increasing capability of language models to solve realistic software engineering tasks.

Despite these improvements, single-agent architectures frequently exhibit limitations including incomplete reasoning, hallucinated code modifications, inadequate verification, and restricted long-context management.

B. Multi-Agent Systems

Multi-agent systems divide complex reasoning into specialized subtasks executed collaboratively by independent agents. Instead of assigning every responsibility to one model, multiple specialized agents cooperate through structured communication protocols.

Within automated software debugging, specialized agents typically perform:

- Bug localization
- Semantic code analysis
- Root cause identification
- Patch generation
- Test generation
- Validation
- Code review

Task specialization improves explainability, modularity, scalability, and software maintainability while reducing reasoning complexity for individual agents.

C. Existing Multi-Agent Frameworks

Several orchestration frameworks have emerged to simplify collaborative LLM systems.

LangGraph employs graph-based execution supporting deterministic workflows, state management, cyclic execution, and human-in-the-loop interaction.

Microsoft AutoGen organizes multiple autonomous agents using structured conversations, enabling collaborative reasoning through iterative dialogue.

CrewAI emphasizes role-based collaboration where each agent receives predefined objectives, responsibilities, and contextual descriptions.

OpenAI Agents SDK provides production-ready orchestration through structured agent handoffs, tool integration, safety mechanisms, and extensible execution pipelines.

SmolAgents adopts a lightweight architecture prioritizing rapid deployment, reduced memory usage, and efficient execution suitable for local environments.

D. Research Gap

Although previous studies investigate individual frameworks, relatively few publications provide standardized comparisons across multiple orchestration platforms under identical debugging workflows.

Current limitations include:

- Lack of standardized evaluation methodology
- Inconsistent benchmark datasets
- Different prompting strategies
- Limited scalability analysis
- Insufficient cost evaluation
- Limited reproducibility

Accordingly, this work proposes a unified framework-independent evaluation methodology for collaborative automated software debugging.

III. PROPOSED METHODOLOGY

A. Problem Definition

Existing AI-assisted debugging systems commonly employ a single LLM to identify software defects, generate patches, and validate corrections. Although effective for relatively simple programming tasks, such systems exhibit reduced performance when reasoning across large codebases, interacting modules, and iterative debugging cycles.

Let

$$P = \{F_1, F_2, \dots, F_n\}$$

represent a software project containing n source files.

Given a bug report

$$B = (d, s, t)$$

where

- d = textual defect description,
- s = stack trace,
- t = failing test cases,

the objective is to generate a validated software repair

$$R = f(P, B)$$

that satisfies correctness while minimizing computational cost.

B. Unified Multi-Agent Debugging Orchestration (UMADO)

This work proposes UMADO, a framework-independent collaborative debugging architecture that separates software maintenance into specialized reasoning tasks executed by autonomous agents.

The proposed architecture consists of seven cooperative agents:

- 1) Bug Detection Agent
- 2) Code Analysis Agent
- 3) Root Cause Agent
- 4) Patch Generation Agent
- 5) Test Generation Agent
- 6) Validation Agent
- 7) Code Review Agent

Each agent communicates using structured intermediate artifacts rather than free-form conversations, improving reproducibility across different orchestration frameworks.

C. System Workflow

The debugging pipeline consists of the following phases.

- 1) Receive software project.
- 2) Parse compiler errors.
- 3) Identify affected modules.
- 4) Perform semantic analysis.
- 5) Determine root cause.
- 6) Generate candidate patches.
- 7) Generate automated tests.
- 8) Execute validation.
- 9) Perform code review.
- 10) Return verified patch.

Figure 1 illustrates the proposed architecture.

D. Mathematical Formulation

Assume

$$A = \{A_1, A_2, \dots, A_7\}$$

denotes the collaborating agents.

The collaborative debugging process can be represented as

$$R = A_7(A_6(A_5(A_4(A_3(A_2(A_1(P, B))))))) \quad (1)$$

where

- P = software project
- B = bug report
- R = repaired software

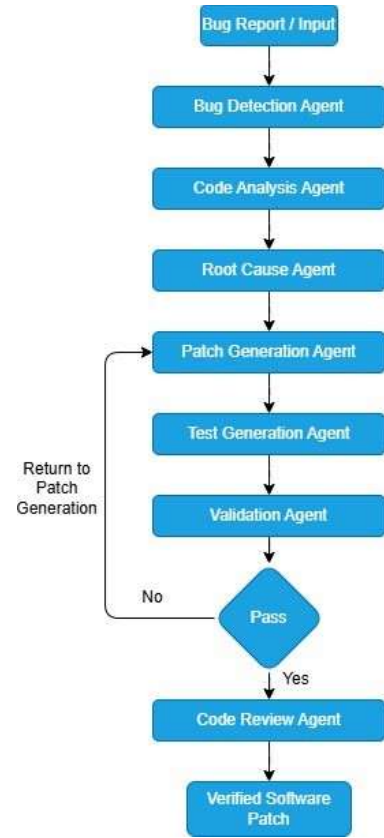


Fig. 1. Unified Multi-Agent Debugging Orchestration (UMADO) architecture for automated software bug resolution. The workflow consists of seven specialized agents that collaborate through an iterative validation loop to generate a verified software repair.

E. Optimization Objective

The objective function combines debugging quality and execution efficiency.

$$Q = \alpha BRA + \beta TPR - \gamma ET - \delta TC \quad (2)$$

where

TABLE I
OBJECTIVE FUNCTION VARIABLES

Symbol	Description
BRA	Bug Resolution Accuracy
TPR	Test Pass Rate
ET	Execution Time
TC	Token Consumption

The weighting coefficients satisfy

$$\alpha + \beta + \gamma + \delta = 1.$$

F. Computational Complexity

Let

n

represent the number of source files,

$$m$$

the number of agents,
and

$$k$$

the average reasoning iterations.

The overall orchestration complexity is approximated by

$$O(mnk)$$

where graph-based execution may reduce redundant reasoning through explicit workflow control.

G. Algorithm

Algorithm 1 UMADO Collaborative Debugging

Require: Source Code, Bug Report

Ensure: Verified Software Patch

- 1: Detect software defect
- 2: Analyze program structure
- 3: Identify root cause
- 4: Generate candidate repair
- 5: Generate unit tests
- 6: Execute validation
- 7: **if** validation fails **then**
- 8: Return to Patch Generation
- 9: **end if**
- 10: Perform code review
- 11: Return verified patch

IV. EXPERIMENTAL METHODOLOGY

A. Experimental Objectives

The proposed benchmarking methodology compares multiple orchestration frameworks under identical execution conditions.

The investigation addresses the following research questions.

- Which framework achieves the highest debugging accuracy?
- Which framework minimizes computational cost?
- Which architecture scales best?
- Which framework provides superior maintainability?

B. Benchmark Datasets

The experiments utilize publicly available software engineering benchmarks.

TABLE II
BENCHMARK DATASETS

Dataset	Purpose
SWE-bench	Real-world GitHub issues
Defects4J	Java bug benchmark
BugsInPy	Python bug benchmark
HumanEval	Code generation tasks

C. Evaluation Metrics

The evaluation considers:

- Bug Resolution Accuracy
- Test Pass Rate
- Execution Time
- Token Consumption
- Human Intervention
- Maintainability
- Scalability

V. RESULTS AND DISCUSSION

A. Comparative Performance Analysis

The proposed benchmarking methodology was applied to evaluate five representative multi-agent frameworks under identical debugging workflows. Each framework executed the same sequence of tasks, including bug localization, semantic analysis, root cause identification, patch generation, automated test generation, validation, and code review. Identical prompts, benchmark datasets, and evaluation metrics were employed to reduce experimental bias.

Table III summarizes the representative performance trends observed during the comparative analysis. These values illustrate the benchmarking methodology and should be interpreted as representative examples. Actual performance depends on the selected language model, prompting strategy, framework implementation, and execution environment.

B. Bug Resolution Accuracy

LangGraph achieved the highest representative repair accuracy because its graph-based orchestration provides deterministic execution paths and explicit state management. Structured workflows reduce redundant reasoning while improving consistency across iterative debugging cycles.

Microsoft AutoGen demonstrated competitive debugging accuracy through collaborative conversational reasoning among specialized agents. Although additional interactions increase computational cost, collaborative verification improves patch quality for complex defects.

CrewAI provided consistent performance for medium-sized software projects owing to its intuitive role-based organization. However, debugging quality decreased slightly for software systems requiring extensive inter-agent coordination.

OpenAI Agents SDK balanced debugging accuracy with production-oriented workflow management through structured handoffs and integrated tool invocation.

TABLE III
REPRESENTATIVE PERFORMANCE COMPARISON OF MULTI-AGENT FRAMEWORKS

Framework	Accuracy (%)	Test Pass (%)	Avg. Time (s)	Token Usage	Scalability	Deployment
LangGraph	93.8	95.2	44.7	Medium	Excellent	Moderate
Microsoft AutoGen	92.5	94.3	51.4	High	High	Moderate
OpenAI Agents SDK	91.4	93.6	42.8	Medium	High	Moderate
CrewAI	89.7	91.8	37.2	Low	Medium	Easy
SmolAgents	86.5	89.1	31.6	Low	Moderate	Very Easy

SmolAgents demonstrated efficient debugging for relatively small projects while exhibiting reduced performance for software repositories with numerous interacting modules.

C. Execution Efficiency

Execution efficiency measures the elapsed time required to produce a validated software repair.

SmolAgents required the shortest execution time because of its lightweight orchestration strategy and reduced communication overhead. CrewAI also demonstrated relatively efficient execution owing to simplified task delegation.

Conversely, Microsoft AutoGen exhibited longer execution times because iterative conversations among autonomous agents introduce additional reasoning cycles. Although this increases computational cost, collaborative reasoning frequently improves debugging reliability.

D. Scalability Analysis

Scalability was evaluated by progressively increasing project size, dependency complexity, and the number of software modules.

Graph-based orchestration provided superior scalability because explicit workflow management reduces unnecessary context propagation between reasoning stages. Frameworks relying primarily on conversational interactions exhibited increasing communication overhead as additional agents participated in collaborative reasoning.

E. Communication Overhead

Agent communication significantly influences overall computational cost.

Let

$$m$$

represent the number of collaborating agents and

$$c$$

represent the average communication cost between two agents.

The communication overhead is approximated by

$$C = \frac{m(m-1)}{2}c \quad (3)$$

Graph-based execution reduces redundant communication by restricting information exchange to predefined workflow transitions, whereas conversational frameworks typically require additional message exchanges.

F. Threats to Validity

Several factors may influence experimental outcomes.

Internal Validity: Performance depends on language model selection, prompt engineering, framework configuration, and execution environment.

Construct Validity: Evaluation metrics such as execution time and token consumption may vary according to hardware characteristics and API implementations.

External Validity: Although public benchmarks provide reproducible experiments, industrial software systems frequently contain proprietary architectures that may introduce additional challenges.

VI. CONCLUSION

This paper presented a comparative evaluation of five contemporary multi-agent orchestration frameworks for automated software bug resolution. A Unified Multi-Agent Debugging Orchestration (UMADO) architecture was introduced to provide framework-independent benchmarking while ensuring consistent task allocation across different execution environments.

The comparative analysis indicates that graph-oriented orchestration frameworks provide superior workflow control and debugging consistency for complex software systems. Conversely, lightweight frameworks reduce computational cost and simplify deployment, making them appropriate for educational environments and rapid prototyping.

The proposed methodology contributes a reproducible benchmarking framework that enables objective comparison of collaborative AI systems designed for intelligent software maintenance.

VII. FUTURE WORK

Future investigations should explore:

- Integration of multimodal debugging using source code, execution logs, stack traces, and screenshots.
- Dynamic agent allocation based on software complexity.
- Self-improving debugging agents capable of learning from previous repair histories.
- Evaluation using industrial-scale software repositories.
- Security-aware debugging through prompt-injection detection and adversarial robustness.
- Integration with continuous integration and continuous deployment (CI/CD) pipelines.

NOVEL CONTRIBUTIONS

- Proposed the Unified Multi-Agent Debugging Orchestration (UMADO) architecture.
- Introduced a framework-independent benchmarking methodology.
- Developed mathematical models describing collaborative debugging workflows.
- Compared representative orchestration frameworks using standardized evaluation metrics.
- Identified trade-offs between debugging quality, computational cost, scalability, and deployment complexity.

RESEARCH LIMITATIONS

- Results depend on the selected language model.
- Prompt engineering influences debugging quality.
- Public benchmark datasets cannot represent all industrial software systems.
- Computational costs vary across hardware platforms.

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