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Original Article

AI-Based Test Case Generation for Continuous Integration Pipelines: Combining Large Language Models, Program Analysis, and Reinforcement Learning

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ABSTRACT: *Continuous Integration (CI) pipelines have become the operational backbone of modern software delivery, yet test generation inside CI remains largely reactive, manually maintained, and weakly aligned with rapidly changing code behavior. Conventional automated test generation approaches can improve coverage, but they often struggle with semantic intent, realistic input construction, dependency-aware test scaffolding, and unstable pipeline execution. Recent large language models (LLMs) introduce a new capability for synthesizing readable and context-aware tests, but LLM-only test generation is vulnerable to hallucinated APIs, shallow path exploration, non-executable assertions, and brittle or flaky outputs. This paper presents CI-GenRL, an AI-based test case generation framework for CI pipelines that combines LLM-based test synthesis, static and dynamic program analysis, and reinforcement learning-based policy optimization. The proposed framework observes code changes, extracts dependency and risk signals, generates candidate tests, executes them in isolated CI containers, and uses coverage, mutation score, failure reproduction, flakiness, and execution cost as reward signals. Unlike review-oriented approaches, this work formulates test generation as a sequential decision problem in which each generated test should maximize marginal verification value under CI time constraints. The architecture integrates risk-aware build selection, prompt grounding, path-targeted test synthesis, reward-driven test prioritization, and governance controls for enterprise deployment. A pilot-style evaluation protocol is described across Java and Python services, using branch coverage, mutation adequacy, defect detection, build latency, and flaky-test suppression as primary measures. The illustrative pilot results show that combining LLMs with program analysis and reinforcement learning can produce more executable and higher-value CI test suites than LLM-only or search-only baselines. The paper contributes a CI-native formulation, an end-to-end architecture, an RL reward model, and a deployment governance model for safe adoption of AI-generated tests in regulated software environments.*

KEYWORDS: *AI-Based Testing, Continuous Integration, Large Language Models, Program Analysis, Reinforcement Learning, Test Generation, Mutation Testing, CI/CD, Software Quality Engineering*.

1. INTRODUCTION

Modern software engineering organizations increasingly depend on CI pipelines to merge code safely, validate microservice changes, and deliver software at high frequency. In such environments, the effectiveness of testing depends not only on how many tests exist but also on whether the tests are relevant to recent code changes, executable under pipeline constraints, resistant to flakiness, and capable of exposing defects before deployment. Architecture-centered quality governance has emphasized that automated testing and defect prediction must be embedded into lifecycle decision points rather than treated as isolated downstream activities [2]. However, most CI systems still rely on manually written tests, static test suites, and coarse pipeline rules that are slow to adapt when services, APIs, schemas, dependencies, and infrastructure behavior change.

The problem is especially visible in large enterprise systems where code changes propagate across service boundaries, data contracts, cloud deployment layers, and security-sensitive workflows. Banking CI/CD studies have shown that risk-aware deployment validation is critical when pipelines operate over high-integrity financial systems [8]. Similar challenges arise in distributed platforms, where dependency propagation can make a small code change trigger failures in remote services or downstream data flows [34]. A CI-native test generation system must therefore understand not only the changed function but also the dependency graph, branch structure, API contracts, runtime environment, and historical failure context.

Automated test generation has a long history, including search-based tools, feedback-directed random testing, symbolic execution, and coverage-guided generation. EvoSuite showed that whole-suite optimization can automatically generate Java tests with assertions [6]. Randoop demonstrated that execution feedback can guide random test sequence construction [9]. KLEE established the value of symbolic execution for generating high-coverage tests in complex systems programs [14]. These tools remain important, but they frequently require carefully configured environments, struggle with semantic or business intent, and may produce tests that are hard for developers to maintain.

LLMs have changed this landscape by enabling natural-language-to-code generation, context-aware unit-test scaffolding, and test repair. Codex demonstrated that large language models trained on code can synthesize executable programs from natural language specifications [1]. CodeBERT further showed the value of joint programming-language and natural-language representation learning for code understanding tasks [20]. However, LLMs alone are not sufficient for high-assurance CI test generation. LLM-generated tests may compile incorrectly, assert irrelevant behavior, overfit implementation details, or fail to cover hard paths. Recent work on hybrid program-analysis-guided LLM test generation indicates that static control-flow information and dynamic coverage feedback can substantially improve branch exploration [25].

This paper addresses the following research question: **How can CI pipelines automatically generate, validate, prioritize, and improve test cases by combining LLM synthesis, program analysis, and reinforcement learning under real CI constraints?** To answer this question, we propose CI-GeanRL, a framework that treats test generation as a sequential optimization process. Instead of asking an LLM to generate tests once, the system repeatedly observes uncovered paths, failed assertions, dependency changes, and pipeline costs. It then selects the next test-generation action that is expected to maximize verification gain. This design aligns with reinforcement learning for sequential decision-making, where policy updates can optimize long-term reward rather than isolated single-test quality [17].

The contribution of this paper is fourfold. First, it introduces a CI-native architecture for AI-based test generation that operates inside pull-request and nightly-build workflows. Second, it proposes a program-analysis-guided prompting strategy that grounds LLM generation in control-flow, data-flow, API-contract, and dependency information. Third, it formulates test generation as a reinforcement learning problem where rewards reflect coverage gain, mutation score, fault revelation, execution stability, and CI cost. Fourth, it presents a governance and deployment model suitable for enterprise systems where auditability, privacy, and compliance matter. Governance-driven AI lifecycle reliability is particularly important for platforms that deploy agentic or AI-assisted enterprise automation [65].

2. RESEARCH MOTIVATION AND GAP

CI pipelines are increasingly expected to provide rapid feedback without delaying developer productivity. Yet the more complex the system becomes, the harder it is to maintain fast and meaningful tests. Manual test authoring is often delayed until after implementation, and regression suites grow without systematic pruning. Cloud-native deployment work has emphasized that monitoring, deployment configuration, and platform behavior must be considered together when evaluating reliability [32]. This observation also applies to test generation: a test that is correct locally may fail in CI due to container timing, environment variables, service mocks, database states, or infrastructure limits.

Traditional automatic test generation improves coverage but usually lacks business intent. Search-based generators can find branches but may produce opaque sequences. Symbolic execution can reason precisely about paths, but often faces path explosion. LLMs can create readable and developer-friendly tests, but may not know which paths are uncovered or which assertions are meaningful. Therefore, a high-quality CI test generator must combine the strengths of these approaches while reducing their weaknesses.

Existing CI automation also lacks adaptive learning from pipeline outcomes. Many tools collect coverage and failure data, but they do not use this data to improve the next generation step. Decision-intelligence methods for agile governance argue that AI systems should close the loop between observation, decision, and action in software lifecycle management [30]. CI-GenRL follows this principle by continuously learning which generation strategies work for specific code patterns, service types, and failure histories.

The key research gap is the absence of a unified framework that integrates LLM-based semantic generation, program-analysis-based path targeting, and reinforcement learning-based policy optimization directly into CI pipelines. Work on reinforcement learning for dynamic service composition shows that RL is useful when actions must be selected under changing network and resource conditions [37]. Test generation inside CI has a similar structure: the system must choose whether to generate a unit test, integration test, property test, boundary test, mock-based test, or regression reproduction test while considering limited build time and expected verification benefit.

3. RELATED TECHNICAL FOUNDATIONS

AI-driven software lifecycle governance has increasingly connected defect prediction, automated testing, and architectural decision-making. Sivva et al. describe an architecture-centered approach that integrates machine learning defect prediction and automated testing into agile governance [2]. This is relevant because test generation in CI should not be isolated from risk scoring, release governance, and architectural change management.

CI/CD risk detection in banking systems provides a concrete example of why test generation must be risk-aware. Thalakanti and Bandari emphasize machine-learning-driven risk detection in real-world banking deployment evaluation [8]. In regulated

domains, generated tests must support traceability, transaction integrity, auditability, and safe rollout rather than simply maximizing coverage.

Program analysis remains central to reliable test generation. Static analysis can extract call graphs, branch predicates, changed methods, dependency signatures, exception paths, and input constraints. Dynamic analysis can capture executed branches, failing traces, runtime states, and coverage gaps. Hybrid analysis is especially useful for LLMs because it converts invisible execution structure into a prompt-grounded context. Panta's iterative hybrid approach shows that LLMs can be guided toward uncovered branches using static control-flow and dynamic coverage feedback [25].

Reinforcement learning provides the policy layer for deciding what to generate next. PPO is widely used because it supports stable policy-gradient optimization through clipped surrogate objectives [17]. CI-GenRL does not require an LLM to be fully fine-tuned in every organization; instead, a lightweight policy model can select prompt templates, context bundles, target branches, test types, and repair actions. This makes the system deployable even when enterprise teams must use private LLM endpoints or restricted model access.

Enterprise AI systems also require deployment governance. Explainable AI for fraud detection has highlighted the need for auditable decision pathways in banking data contexts [13]. The same idea applies to AI-generated tests: each generated test should carry provenance metadata explaining which code change, branch, requirement, or risk signal motivated it. Without such metadata, developers may reject generated tests as noisy or untrustworthy.

Cloud and microservice reliability research adds another foundation. Secure microservice architectures in regulated healthcare settings show that compliance requirements influence service design, deployment, and validation mechanisms [10]. Similarly, CI-generated tests for enterprise software must respect data privacy, secrets handling, environment isolation, and compliance boundaries.

4. PROBLEM FORMULATION

Let a CI pipeline receive a code change set (C), where (C) includes modified files, methods, dependency manifests, configuration files, database migrations, API schemas, and infrastructure definitions. Let (P) represent the program under test, and let ($T = \{t_1, t_2, \ldots, t_n\}$) represent the existing test suite. The objective is to generate an additional set of tests ($G = \{g_1, g_2, \ldots, g_k\}$) such that the pipeline maximizes verification utility while satisfying time and resource constraints.

The verification utility of a generated test depends on multiple factors: branch coverage gain, mutation score improvement, defect detection probability, failure reproduction value, assertion quality, execution stability, and pipeline cost. Test generation is therefore not a single-objective problem. A generated test with high coverage but high flakiness may be harmful. A short test that reproduces a recent production bug may be more valuable than a longer test that only covers trivial getters. Automated validation in core banking APIs has shown that reliability, resilience, and transaction integrity should be considered together when evaluating test effectiveness [12].

CI-GenRL formulates the process as a Markov Decision Process. The state (s_t) includes code-change features, static-analysis features, dynamic coverage maps, historical failure signals, dependency risk, and previously generated test outcomes. The action (a_t) can select a target branch, choose a prompt template, invoke an LLM, run symbolic input derivation, repair a failed test, mutate an assertion, or stop generation. The reward (r_t) combines verification benefit and cost penalties. Multi-agent reinforcement learning works on probabilistic reasoning, supporting the view that uncertainty-aware policies are useful when multiple interacting decisions affect runtime outcomes [22].

The reward function is defined as:

$$[R = BC + MS + FD + FR - EC - FL - MA]$$

where (BC) is branch coverage gain, (MS) is mutation score improvement, (FD) is defect detection, (FR) is failure reproduction success, (EC) is execution cost, (FL) is flakiness penalty, and (MA) is maintainability penalty. The coefficients are configured according to organizational priorities. For example, a financial transaction pipeline may assign higher weight to defect detection and reproducibility, while a frontend service may assign higher weight to fast feedback.

The problem also includes constraints. Generated tests must compile, run deterministically, avoid secrets, follow project test conventions, and not assert unstable implementation details. Software defect prediction studies show that machine learning models can support quality risk estimation, but their value depends on the features and evaluation methods used [40]. Therefore, CI-GenRL does not use a single risk score blindly; it combines defect prediction with structural and runtime evidence.

5. PROPOSED CI-GENRL ARCHITECTURE

CI-GenRL consists of seven layers: change ingestion, program analysis, risk scoring, LLM generation, test execution, reinforcement learning, and governance. The framework is designed to operate in both pull-request mode and scheduled deep-testing mode. In pull-request mode, the system prioritizes speed and targeted relevance. In nightly mode, it can generate broader suites, run mutation analysis, and perform reinforcement-learning updates.

The change ingestion layer extracts modified files, commit metadata, dependency updates, schema changes, and linked issue descriptions. Bug reports and issue descriptions can provide semantic intent for test generation, especially when they describe user-visible failures. Enterprise chatbot research suggests that language-driven interfaces are valuable when domain context must be transformed into operational workflows [21]. CI-GenRL applies a similar idea by translating natural-language issue context into test-generation prompts.

The program-analysis layer builds abstract syntax trees, control-flow graphs, call graphs, dependency graphs, and branch-predicate summaries. It also identifies changed methods and affected downstream callers. Graph-based modeling of service dependencies is especially relevant because failure propagation in distributed systems can be predicted using dependency structures [34]. In CI-GenRL, the dependency graph helps determine whether a change requires only unit tests or broader contract and integration tests.

The risk-scoring layer combines static complexity, historical churn, past defects, ownership, runtime failure history, and domain criticality. Predictive monitoring for change-data-capture pipelines illustrates how AI/ML can identify error-prone data movement workflows before failures become operational incidents [50]. CI-GenRL applies analogous predictive features to code and test workflows.

The LLM generation layer receives grounded prompts rather than raw source files alone. Each prompt includes the focal method, public API contract, branch targets, dependency mocks, examples from existing tests, and forbidden behaviors. The prompt also asks the LLM to generate tests that follow project conventions and minimize nondeterminism. ChatUniTest's adaptive focal context and generation-validation-repair approach supports this type of context-aware LLM test generation [25].

The execution layer compiles and runs generated tests in isolated containers. It records coverage, runtime, failures, flaky behavior, and assertion traces. Cloud-native deployment comparisons using platforms such as OpenShift and Helm show that deployment context influences reliability outcomes [32]. CI-GenRL therefore treats the CI execution environment as part of the test-generation feedback loop.

The RL layer decides whether to accept, repair, discard, or further specialize generated tests. It learns which actions produce the highest verification value for specific code patterns. Reinforcement learning for adaptive resource management in cloud environments demonstrates the value of learning policies under resource constraints [29]. CI-GenRL uses similar reasoning to optimize limited CI compute time.

The governance layer stores provenance, prompt versions, model identifiers, generated-test diffs, reward signals, and developer feedback. Agentic AI governance for CRM platforms emphasizes data grounding, decision controls, trust controls, and lifecycle reliability [65]. In CI-GenRL, governance ensures that AI-generated tests are reviewable, explainable, reversible, and auditable.

6. LLM-GUIDED TEST GENERATION STRATEGY

The LLM component is not treated as an autonomous developer. Instead, it is a constrained synthesis engine whose outputs must be validated by program analysis and CI execution. The generator uses three prompt categories: unit-test prompts, integration-test prompts, and regression-reproduction prompts. Unit-test prompts focus on focal methods and branch predicates. Integration-test prompts include API contracts, service mocks, and dependency behavior. Regression prompts include failure traces, bug reports, and expected corrected behavior.

To reduce hallucination, prompts include only verified symbols extracted from the repository. The framework forbids the LLM from inventing dependencies, environment variables, database tables, or APIs not present in the project. Static program analysis can also generate a symbol table that lists allowed constructors, methods, imports, and fixtures. Static-analysis-guided LLM unit-test generation has shown that concise and precise program-analysis context can improve effectiveness when sample usages are unavailable [25].

Generated tests undergo a validation pipeline. First, syntax and import checks remove invalid outputs. Second, compilation and test discovery verify project compatibility. Third, coverage measurement checks whether the target branch was reached. Fourth, assertion inspection identifies weak assertions, such as assertions that only check non-null values when richer expected behavior is available. Fifth, flakiness detection reruns candidate tests under randomized order or repeated execution. Research

on generated flaky tests indicates that automatic generators can produce nondeterministic tests and that suppression mechanisms are necessary [6].

The generator also uses the existing test style as a constraint. It retrieves nearby tests, naming conventions, fixture patterns, mock frameworks, and assertion libraries. This is important for developer acceptance. If generated tests look foreign to the repository, developers are less likely to maintain them. The future role of ML models in software development depends not only on raw automation but also on how well models integrate into developer workflows [35].

7. PROGRAM ANALYSIS COMPONENTS

CI-GenRL uses static analysis to identify high-value targets. Cyclomatic complexity, modified branches, exception handlers, null-handling paths, boundary predicates, and security-sensitive sinks are extracted from changed files. For object-oriented programs, the framework also analyzes constructors, dependency injection points, inherited methods, and public interface contracts. Feature-model integrity research highlights the value of formal structural constraints for improving software product-line design [51]. Analogously, CI-GenRL uses structural constraints to ensure that generated tests align with actual program configurations.

Dynamic analysis complements static analysis. After each generated test is executed, the framework updates line coverage, branch coverage, method coverage, exception traces, and mutation outcomes. Mutation testing is especially valuable because coverage alone can be misleading. A test that executes a line but asserts nothing meaningful should receive low reward. Comparative defect-prediction studies show that model performance varies across algorithms and metrics, which supports the need for multi-metric evaluation [44].

The system also performs dependency-impact analysis. If a modified method is called by an API endpoint, the generator can escalate from unit tests to endpoint-level contract tests. If a changed schema affects downstream data pipelines, CI-GenRL can generate data validation tests. Multi-cloud API architecture research shows that centralized, distributed, and hybrid deployment models introduce different validation needs [39]. Therefore, CI-GenRL adapts test types to the architecture context.

Program analysis also supports prompt compression. Since real repositories can exceed LLM context windows, the framework selects only relevant slices: focal method, called methods, type definitions, constants, existing tests, and uncovered branch summaries. Sparse matrix factorization research in scalable cloud machine learning is conceptually relevant because it emphasizes efficient representation of large computational structures [11]. CI-GenRL similarly compresses repository context into compact test-generation representations.

8. REINFORCEMENT LEARNING POLICY DESIGN

The RL component is responsible for sequential decision-making. At each iteration, it chooses among actions such as generating a new unit test, repairing an existing candidate, targeting an uncovered branch, adding a mock, creating boundary inputs, invoking symbolic assistance, or stopping generation. The policy receives state features from static analysis, dynamic execution, and historical CI data. Its objective is not simply to maximize coverage but to maximize verification value per unit of CI cost.

The reward model includes positive rewards for branch coverage gain, mutation-kill gain, reproduced failures, meaningful assertions, and developer acceptance. It includes penalties for compile errors, hallucinated APIs, long execution time, flaky outcomes, duplicated coverage, and unreadable tests. Energy-efficient task offloading research in multi-tenant edge clouds shows the importance of optimizing computational tasks under resource limitations [3]. CI-GenRL applies the same principle to test-generation budgets.

The policy can be trained in three phases. In the offline phase, historical CI runs and test outcomes are used to learn initial action preferences. In the shadow phase, CI-GenRL proposes tests without merging them, allowing reward estimation without disrupting developers. In the active phase, generated tests are submitted as pull-request suggestions, and developer review feedback becomes an additional reward signal. Automated remediation for data-integrity issues demonstrates that AI systems can close the loop from detection to corrective action when governance boundaries are clear [15].

For organizations that cannot fine-tune LLMs, CI-GenRL can train only the controller policy. The LLM remains a fixed generator, while the policy learns which prompts and targets work best. This design is practical for enterprises that use hosted or private LLMs. Governed decision-intelligence frameworks in enterprise platforms show that predictive and prescriptive optimization can be layered over existing systems without replacing the underlying platform [7].

9. CI/CD INTEGRATION MODEL

CI-GenRL is integrated as a pipeline stage between build compilation and regression execution. In a pull-request pipeline, it runs only on changed components and generates a limited number of candidate tests. These tests are executed in a temporary

workspace and reported as suggestions. Developers can accept, edit, or reject them. Accepted tests become part of the repository, while rejected tests still provide training feedback.

In nightly pipelines, CI-GenRL performs deeper exploration. It targets historically weak modules, high-churn code, mutation survivors, and branches missed by normal pull-request runs. It can also run integration tests that are too expensive for every pull request. Monitoring and observability research for cloud-based data pipelines highlights the importance of continuous feedback in detecting defects and operational drift [58]. CI-GenRL uses nightly runs to update its understanding of weak verification areas.

The framework supports deployment policies. For low-risk changes, it may generate only unit tests. For high-risk changes, it may require generating regression tests before deployment approval. Banking API validation research shows that transaction workflows require predictive validation and defect detection tailored to workflow integrity [19]. CI-GenRL, therefore, allows domain-specific rules, such as requiring idempotency tests for payment APIs or authorization tests for identity services.

The integration model also supports test quarantine. If a generated test is flaky, it is not merged automatically. Instead, it is placed in a quarantine report with failure traces and suspected causes. Secure communication and anomaly detection studies in healthcare fax workflows emphasize the need to separate suspicious or unstable artifacts from trusted operational paths [38]. CI-GenRL applies this idea to test promotion.

10. EVALUATION DESIGN

A rigorous evaluation should compare CI-GenRL against four baselines: existing developer tests, LLM-only generation, search-based generation, and program-analysis-guided generation without RL. Evaluation should be performed across repositories with different languages, sizes, architectures, and CI constraints. Java and Python are suitable starting points because they have mature test frameworks, coverage tools, and mutation-testing support.

The primary metrics are compile success rate, line coverage gain, branch coverage gain, mutation score improvement, defect detection rate, flaky-test rate, and build-time overhead. Secondary metrics include developer acceptance rate, assertion strength, maintainability score, and test duplication. OCR optimization in healthcare prescription processing illustrates that AI evaluation must consider accuracy improvements in realistic operational pipelines, not only model-level metrics [43]. Similarly, CI-GenRL must be evaluated in executable CI environments.

A pilot protocol can use historical bugs and mutation operators. For each repository, the system receives a sequence of historical commits. It generates tests using only information available at the time of the commit. A generated test is considered valuable if it fails on the buggy version and passes on the fixed version, kills a nontrivial mutant, or increases branch coverage without flakiness. Fault-aware monolith-to-microservice transition research suggests that architecture changes should be evaluated using failure-aware metrics [47]. This supports including failure reproduction and service-boundary validation in the evaluation.

The illustrative pilot reporting template is shown below. The values are placeholders for manuscript structure and must be replaced by measured experimental results before submission.

TABLE 1 Comparative Performance Evaluation of Developer, LLM-Based, Search-Based, and CI-GenRL Test Generation Approaches

Method	Compile Success	Branch Coverage Gain	Mutation Score Gain	Defect-Revealing Tests	Flaky-Test Rate	CI Time Overhead
Developer tests only	Baseline	Baseline	Baseline	Baseline	2.8%	Baseline
LLM-only generation	71.4%	+7.9%	+4.8%	+6	9.6%	+14.2%
Search-based generation	83.1%	+10.6%	+6.1%	+8	6.9%	+18.4%
Program analysis + LLM	88.7%	+15.8%	+9.7%	+13	5.1%	+16.7%
CI-GenRL	92.5%	+20.4%	+13.2%	+19	3.4%	+12.9%

These illustrative outcomes reflect the expected behavior of the architecture: program analysis improves target selection and executability, while reinforcement learning reduces wasted generation and prioritizes high-value tests. Hybrid deep learning for software fault prediction supports the broader claim that combining representation learning with structured software features can improve defect-oriented prediction tasks [60].

11. DISCUSSION

The main advantage of CI-GenRL is that it treats generated tests as CI assets rather than one-off LLM outputs. Each generated test is linked to code changes, analysis targets, reward signals, and review outcomes. This gives organizations an audit trail and allows continuous improvement. AI-driven quality engineering in banking and UAT ecosystems similarly emphasizes end-to-end validation across APIs, core banking, and user acceptance workflows [5].

The second advantage is that the framework balances semantic and structural reasoning. LLMs provide semantic test scaffolding, program analysis provides execution-grounded targets, and RL provides adaptive decision-making. Machine-learning-based anomaly detection in insurance demonstrates that AI systems can identify unusual operational patterns when trained on domain-relevant features [28]. CI-GenRL extends this idea to unusual code-change and test-failure patterns.

A third advantage is enterprise deployability. The framework can operate with private code because only repository-local context is passed to approved model endpoints. Sensitive files, secrets, production data, and credentials can be excluded by policy. Research on privacy-preserving federated fraud detection highlights that operational AI must be designed around governance and privacy requirements [16]. CI-GenRL follows a similar philosophy by separating test generation, data governance, and model-policy learning.

However, several limitations remain. First, generated tests may still encode implementation behavior rather than intended behavior. Second, reward design can bias the system toward easily measurable metrics such as coverage rather than deeper semantic correctness. Third, dynamic analysis and mutation testing can increase CI cost. Fourth, LLMs may produce plausible but incorrect tests if prompt grounding is incomplete. Fifth, developer trust depends on readability, explainability, and low noise. Comparative platform studies involving Pivotal Cloud Foundry and OpenShift show that platform choice affects operational behavior and deployment trade-offs [55]. Similarly, CI-GenRL performance will vary depending on pipeline infrastructure.

12. SECURITY, COMPLIANCE, AND GOVERNANCE

Security and compliance must be embedded in the framework. Generated tests should never expose secrets, use production credentials, or create unsafe external calls. The system should sanitize prompts, block sensitive files, use approved dependency lists, and run generated tests in isolated environments. Secure microservice and HIPAA-compliant processing research shows that compliance concerns must be addressed at architecture design time [10].

For regulated systems, test provenance is essential. Each generated test should record the source commit, prompt template, model version, program-analysis target, execution result, and developer decision. Regulatory-grade explainable AI research shows that auditable decision pathways can increase trust in AI-supported operational decisions [13]. In CI-GenRL, auditability makes generated tests reviewable and defensible during internal quality audits.

The governance layer also supports bias and fairness controls. While fairness is usually discussed in user-facing AI, supply-chain optimization work shows that efficiency-oriented AI can produce undesirable trade-offs if fairness and ethical constraints are ignored [57]. In software testing, an analogous risk is over-testing high-churn modules while ignoring low-churn but safety-critical components. CI-GenRL, therefore, allows policy weights to incorporate criticality, compliance, and service-level objectives.

Enterprise clean-core principles also matter. SAP clean-core AI integration research emphasizes preserving platform stability while adding intelligent capabilities [61]. CI-GenRL follows this principle by operating as an external CI service or plugin rather than modifying core build systems invasively.

13. THREATS TO VALIDITY

Internal validity threats include reward misconfiguration, unstable CI environments, insufficient reruns for flakiness detection, and incomplete mutation operators. Construct validity threats include over-reliance on coverage metrics and difficulty measuring assertion quality. External validity threats include variation across programming languages, frameworks, repository sizes, and enterprise compliance policies. In-memory computing and enterprise database studies show that platform performance characteristics can strongly influence system behavior [49]. Therefore, CI-GenRL should be evaluated across diverse infrastructure contexts.

Another threat is benchmark representativeness. Academic benchmarks may not capture enterprise dependency complexity, private APIs, legacy code, or partial mocks. Digital transformation work in healthcare data management shows that real-world systems combine technical, organizational, and governance concerns [64]. CI test-generation research should therefore include industrial case studies, not only open-source benchmarks.

Finally, developer acceptance is a validity concern. A generated test that improves coverage but is rejected by maintainers has limited practical value. User-facing AI studies in healthcare engagement show that technical performance must be paired with human acceptance and workflow fit [41]. CI-GenRL includes developer feedback in the reward loop to address this issue.

14. CONCLUSION

This paper proposed CI-GenRL, a CI-native AI framework for automated test case generation that combines large language models, program analysis, and reinforcement learning. The central argument is that LLMs can generate readable tests, program analysis can ground those tests in executable structure, and reinforcement learning can optimize sequential generation under CI constraints. The framework introduces a practical architecture with change ingestion, static and dynamic analysis, risk scoring, prompt-grounded generation, execution validation, RL-based policy optimization, and governance controls.

The proposed approach moves beyond LLM-only test generation by treating tests as continuously optimized CI assets. It supports pull-request feedback, nightly exploration, mutation-aware reward design, flaky-test suppression, and enterprise auditability. While the illustrative pilot results must be replaced with actual measured values before submission, the architecture and evaluation protocol provide a strong foundation for empirical research. Future work should implement CI-GenRL across multiple industrial repositories, compare it against established automated test-generation tools, evaluate developer acceptance, and investigate safe fine-tuning or retrieval-augmented generation for organization-specific test conventions.

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