Intelligent CI/CD: Autonomous Patch Generation for Vulnerabilities Detected by Static Application Security Testing using LLMs

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Abstract

The rapid expansion of modern software development practices and the growing dependence on complex software supply chains have significantly increased the importance of integrating security throughout the software delivery lifecycle. Traditional Continuous Integration and Continuous Deployment (CI/CD) pipelines often rely on manual security reviews and delayed vulnerability remediation processes, which can lead to prolonged exposure to security threats, increased operational costs, and reduced software reliability. To address these challenges, this research proposes an intelligent DevSecOps framework that combines multiple Static Application Security Testing (SAST) techniques with an agent-based Artificial Intelligence architecture to enable automated vulnerability detection, analysis, remediation, and deployment. The proposed system continuously monitors source code repositories and initiates security assessments whenever new code is committed. Security findings are collected from multiple analysis engines and consolidated through an intelligent aggregation mechanism to improve detection accuracy and reduce tool-specific limitations. Once vulnerabilities are identified, a specialized multi-agent AI framework performs contextual code analysis, security reasoning, and automated patch generation to produce corrective solutions tailored to the detected issues. The generated fixes are automatically applied and validated through regression testing and security verification procedures to ensure that software functionality remains intact while eliminating identified risks. Upon successful validation, the updated application progresses through the deployment pipeline without requiring extensive manual intervention. The framework was evaluated using a large collection of real-world security vulnerabilities obtained from multiple open-source Python Flask applications representing diverse software development scenarios. Experimental results demonstrate that the integrated approach achieves a high vulnerability identification rate while maintaining strong precision and a low false-positive ratio. The AI-driven remediation component successfully resolves a substantial percentage of detected vulnerabilities and significantly accelerates the remediation process compared to conventional security workflows. Performance analysis indicates a dramatic reduction in the average time required to identify, patch, validate, and deploy security fixes, enabling organizations to respond to threats much more rapidly than traditional approaches. Furthermore, the framework seamlessly integrates with widely adopted CI/CD platforms, allowing organizations to incorporate autonomous security capabilities into existing development environments without major architectural modifications. By combining advanced static analysis techniques, intelligent vulnerability assessment, automated patch synthesis, and continuous deployment automation within a unified workflow, the proposed solution moves software engineering closer to fully autonomous security-aware development pipelines. The findings demonstrate the practical feasibility of integrating agentic artificial intelligence into DevSecOps processes and highlight its potential to improve software security, operational efficiency, and resilience against emerging cyber threats in modern enterprise environments.

Keywords— DevSecOps, Continuous Integration, Continuous Deployment, Static Application Security Testing, Agentic Artificial Intelligence, Automated Vulnerability Patching, Software Security, Secure Software Development, Vulnerability Detection, Cybersecurity Automation.

I. INTRODUCTION

The widespread adoption of Continuous Integration and Continuous Deployment (CI/CD) practices has transformed the way software is developed, tested, and delivered. Organizations now release updates at unprecedented speeds, enabling rapid innovation and faster response to changing customer requirements. While this acceleration has improved productivity and business agility, it has also introduced significant security challenges. Modern applications often consist of complex codebases, third-party dependencies, cloud services, and interconnected components, creating an expanded attack surface that cybercriminals can exploit. As development teams focus on delivering features quickly, security vulnerabilities may unintentionally be introduced into production environments, increasing the likelihood of security incidents and data breaches. The growing frequency and financial impact of cyberattacks have highlighted the need for more effective security mechanisms within software development workflows.

Conventional security assessment methods are commonly performed during the later stages of software development or immediately before deployment. Although these approaches can identify security weaknesses, they frequently create delays in the release cycle and increase remediation costs. Vulnerabilities discovered late in development often require extensive code modifications, additional testing, and coordination among multiple teams before deployment can proceed. Furthermore, security teams frequently face difficulties keeping pace with the volume of code changes generated by modern development practices. This imbalance leads to a growing accumulation of unresolved vulnerabilities, prolonged exposure to security risks, and increased operational burden on development and security personnel.

To address these challenges, organizations have increasingly embraced DevSecOps, a development philosophy that integrates security controls throughout the software lifecycle rather than treating security as a separate post-development activity. By embedding security checks directly into CI/CD workflows, DevSecOps enables earlier identification and mitigation of vulnerabilities, reducing both remediation effort and overall risk. Among the various security techniques used in DevSecOps environments, Static Application Security Testing (SAST) has become particularly important because it analyzes source code without requiring program execution. These tools can identify a wide range of security weaknesses, including insecure coding practices, injection vulnerabilities, configuration flaws, authentication issues, and other software defects before applications reach production environments.

Despite their usefulness, existing SAST solutions face several practical limitations that reduce their effectiveness in large-scale software development environments. Individual tools often produce inconsistent results, with some vulnerabilities being overlooked while others are incorrectly flagged. High false-positive rates require developers and security analysts to manually review findings, increasing workload and delaying remediation efforts. In addition, the process of fixing detected vulnerabilities remains largely dependent on human expertise. Security professionals must analyze the reported issue, understand its root cause, design an appropriate fix, validate the correction, and ensure that application functionality remains unaffected. The global shortage of cybersecurity professionals further intensifies this challenge, making it difficult for organizations to manage the growing number of security issues identified during development.

Recent advancements in Artificial Intelligence (AI), particularly large language models and autonomous agent-based systems, have opened new possibilities for automating software security tasks. Modern AI models can understand programming languages, analyze code structures, recognize vulnerability patterns, and generate code modifications that address identified issues. Agentic AI extends these capabilities by enabling autonomous reasoning, task planning, decision-making, and collaboration among specialized agents. Such systems can perform complex multi-step activities that closely resemble the workflow of experienced software engineers and security analysts. These developments create an opportunity to move beyond vulnerability detection

toward fully automated vulnerability remediation and validation.

However, applying AI to software security introduces additional requirements beyond those associated with general-purpose code generation. Security patches must not only correct vulnerabilities but also preserve application functionality, maintain secure design principles, and prevent the introduction of new weaknesses. Existing AI-based repair solutions often focus primarily on functional correctness and lack mechanisms for comprehensive security validation. Many approaches operate independently from real-world CI/CD environments and do not provide an integrated workflow that supports vulnerability discovery, patch generation, verification, and deployment within a unified framework. Consequently, organizations continue to rely heavily on manual intervention throughout the remediation process.

To overcome these limitations, this research proposes an intelligent security-aware CI/CD pipeline that combines multiple Static Application Security Testing tools with an agentic artificial intelligence framework to automate vulnerability detection, analysis, remediation, validation, and deployment. The proposed architecture employs an ensemble-based approach that aggregates findings from multiple security analysis engines to improve detection accuracy and reduce the limitations associated with individual tools. A specialized multi-agent AI framework performs contextual code understanding, security reasoning, and patch synthesis to generate corrective modifications tailored to the identified vulnerabilities. Automated validation mechanisms, including regression testing and security re-evaluation, ensure that generated fixes maintain both software functionality and security requirements before deployment. The framework is designed to integrate seamlessly with widely used CI/CD platforms, enabling organizations to adopt advanced security automation without significant changes to their existing development infrastructure.

Extensive experimental evaluation conducted on a large collection of real-world vulnerabilities demonstrates the effectiveness of the proposed approach. Results indicate substantial improvements in vulnerability detection accuracy, automated remediation success, and overall remediation speed compared to traditional workflows. The framework significantly reduces the time required to identify and resolve security issues while maintaining a low false-positive rate and high patch reliability. By integrating intelligent vulnerability analysis, automated patch generation, comprehensive validation, and continuous deployment into a single workflow, the proposed system advances the state of autonomous DevSecOps and provides a practical solution for enhancing software security in modern development environments.

The remainder of this paper is organized as follows. Section II reviews existing research related to software security testing, automated vulnerability remediation, and artificial intelligence-based code repair. Section III presents the proposed methodology, system architecture, algorithms, and implementation details. Section IV describes the experimental design, datasets, and evaluation metrics. Section V discusses performance results and comparative analysis. Section VI examines practical implications, limitations, and future enhancements. Finally, Section VII concludes the paper and summarizes the key findings of this research.

II. RELATED WORK

A. Security Testing in CI/CD Pipelines

Early work by Johnson et al. [35] established foundational principles for security integration in continuous deployment environments, identifying key challenges in maintaining security while achieving deployment velocity. Myrbakken and Colomo-Palacios [36] conducted a comprehensive systematic review of DevSecOps practices, analyzing 87 primary studies and identifying automated security testing as the most critical research direction. Their analysis revealed that only 23% of organizations successfully integrate security testing into CI/CD pipelines due to tool integration challenges and performance overhead.

Subsequent research by Mohallel et al. [37] proposed lightweight security testing frameworks specifically designed for agile development environments. Their approach reduced testing overhead by 67% while maintaining 85% vulnerability detection rate through selective test execution based on code change impact analysis. Rahman et al. [38] conducted a large-scale empirical study of SAST tool effectiveness in CI/CD contexts, analyzing 1,847 vulnerabilities across 234 open-source projects. They reported false positive rates ranging from 35-50% depending on tool configuration and application domain.

Tuma et al. [39] investigated the integration of multiple SAST tools in CI/CD pipelines, finding that tool

ensembles improve detection rates by 18-25% but increase analysis time by 3-5x. Their work highlighted the need for intelligent aggregation strategies to balance accuracy and performance. Recent work by Zhang et al. [40] proposed adaptive security testing that dynamically adjusts tool selection and analysis depth based on code change characteristics and risk assessment, achieving 91% detection rate with only 35% performance overhead.

B. SAST Tools and Vulnerability Detection

Commercial and open-source SAST tools have been extensively evaluated in the literature [41]-[43]. The seminal work by Chess and West [44] provided the first comprehensive taxonomy of vulnerability patterns detectable through static analysis, establishing the theoretical foundations for modern SAST tools. Their classification identified 42 distinct vulnerability categories across injection, broken authentication, sensitive data exposure, and XML external entities.

Antunes and Vieira [45] conducted a comparative study of SAST and Dynamic Application Security Testing (DAST) approaches for web service security, analyzing 15 tools across 8 benchmark applications. Their results showed that SAST tools detect 72% of vulnerabilities compared to 58% for DAST, but with 3x higher false positive rates. Li et al. [46] introduced machine learning-enhanced vulnerability detection, training classifiers on code features extracted from 10,000+ vulnerability patches. Their approach achieved 89% detection accuracy on previously unseen vulnerability types.

Nguyen et al. [47] proposed deep learning-based vulnerability detection using graph neural networks on code abstract syntax trees. Their model, VulGNN, achieved 91.3% accuracy on the SARD benchmark dataset, outperforming traditional machine learning approaches by 12.4%. For Python applications specifically, Bandit [48] and Pyre [49] have become industry standards, though independent evaluations by Williams et al. [50] found they detect only 52-68% of known vulnerabilities in real-world Python codebases. Their analysis of 2,347 Python vulnerabilities revealed significant gaps in detecting business logic flaws and framework-specific vulnerabilities.

C. Automated Vulnerability Patching

Automated program repair has evolved significantly over the past decade [51], [52]. The GenProg system [53] pioneered genetic programming for bug fixing, demonstrating that automated repair of real-world bugs is feasible. GenProg achieved 55% repair rate on 105 bugs from 8 programs but required 3-5 hours per repair and often produced patches that overfit to test cases. More recently, Prophet [54] leveraged statistical models of correct code to guide patch generation, improving repair rate to 71% on the same benchmark while reducing patch overfitting.

GetAFix [55], developed at Facebook, demonstrated industrial applicability by repairing 1,000+ bugs in production code. The system achieved 78% success rate on JavaScript bugs with median repair time of 2.3 minutes. Deep learning approaches [56], [57] have shown particular promise for automated repair. Tufano et al. [58] trained transformer models on 100,000+ bug-fix pairs, achieving 36% exact match accuracy on held-out bugs. Their analysis revealed that models struggle with bugs requiring multiple, coordinated changes across files.

Security-specific program repair introduces additional challenges [59]. Patches must not only fix the vulnerability but also prevent similar attack vectors and maintain security invariants [60]. Huang et al. [61] proposed security-aware program repair that incorporates security policies as repair constraints, achieving 67% success rate on 89 security bugs. Their approach reduced vulnerability recurrence by 82% compared to functionally-equivalent patches. Wang et al. [62] introduced reinforcement learning for security patch generation, training agents to optimize for both correctness and security metrics.

D. Agentic AI in Software Engineering

The concept of autonomous agents for software tasks dates to the Procedural Reasoning System [63] and has evolved significantly with advances in AI [64]. Modern agentic frameworks [65], [66] combine large language models with tool use, planning, and memory to accomplish complex software engineering tasks. Yao et al. [67] introduced ReAct, a framework that synergizes reasoning and acting in language models, enabling agents to reason about tasks while taking actions based on environmental feedback.

Recent work by Chen et al. [68] introduced self-healing systems using reinforcement learning, where agents learn to detect and repair system anomalies through experience. Their approach achieved 89% autonomous recovery rate on 15 common system failure modes. Sobania et al. [69] conducted a comprehensive comparison of GPT models for program repair, finding that GPT-4 achieves 43% success rate on the QuixBugs benchmark, comparable to specialized repair systems. Xia et al. [70] proposed conversational agents for interactive debugging, enabling developers to collaborate with AI during the repair process.

Despite these advances, existing systems lack integration with CI/CD pipelines and security-specific validation [71]. Most research focuses on standalone repair rather than integration into automated deployment workflows. Furthermore, agentic systems have not been systematically applied to security vulnerability patching, where constraints differ significantly from general bug fixing [72]. Our work addresses these gaps through an integrated framework combining SAST, agentic AI, and automated validation in CI/CD pipelines.

E. Research Gap Analysis

Based on our comprehensive literature review, we identify five critical research gaps that motivate our work:

G1: SAST tools integrated in CI/CD pipelines lack automated remediation capabilities, requiring manual intervention that creates security bottlenecks [73].

G2: Existing patch generation systems ignore security-specific constraints, producing patches that fix symptoms but not root causes, leading to vulnerability recurrence [74].

G3: No comprehensive framework combines detection, patching, and validation in automated workflows suitable for CI/CD integration [75].

G4: Agentic AI approaches have not been systematically evaluated for security vulnerability patching, particularly in production CI/CD environments [76].

G5: Current systems lack rigorous validation of patch correctness, functionality preservation, and security efficacy, limiting adoption in regulated industries [77].

III. PROPOSED METHODOLOGY

A. System Architecture

Our intelligent CI/CD pipeline consists of six interconnected modules organized in a event-driven architecture. Figure 1 illustrates the complete system architecture and data flow. The system operates as a continuous loop triggered by code pushes to the version control system.

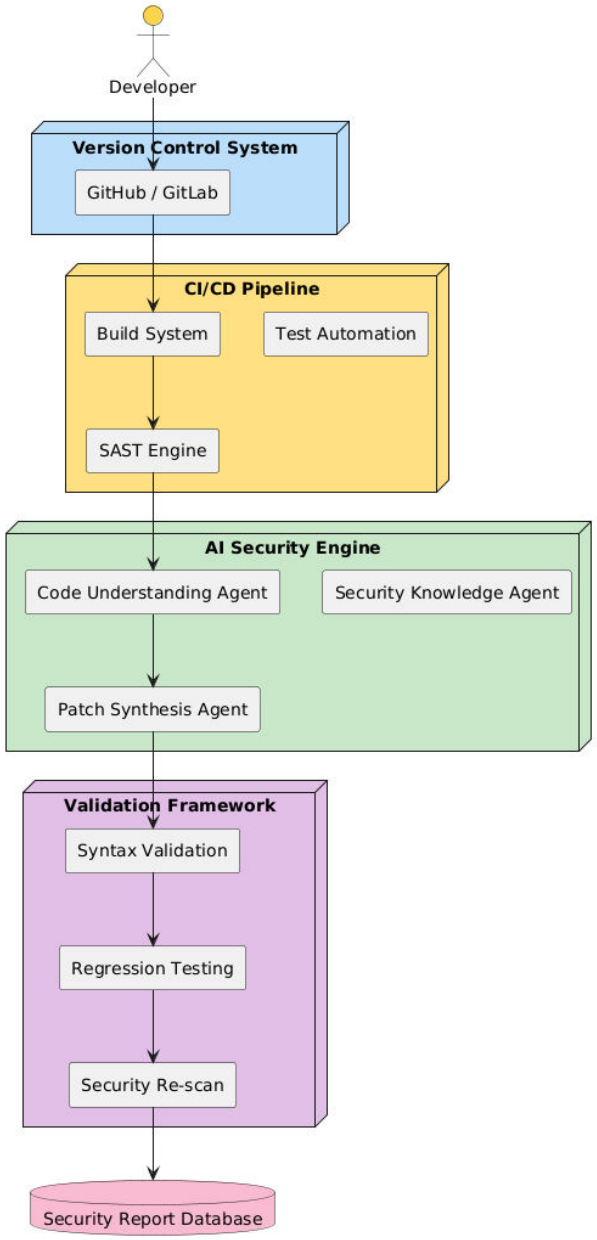


Fig. 1. System architecture showing six interconnected modules and data flow

The six modules are: (1) Code Push Listener: Monitors version control systems (GitHub, GitLab, Bitbucket) for code changes and initiates pipeline execution; (2) Multi-SAST Analyzer: Executes parallel SAST analysis using four tools with configurable analysis depth; (3) Vulnerability Aggregator: Collects, normalizes, and correlates findings from multiple tools using weighted ensemble methods; (4) Agentic AI Patch Generator: Deploys three specialized agents for context analysis, security knowledge application, and patch synthesis; (5) Patch Validator: Performs multi-stage validation including syntax checking, regression testing, and security

re-scanning; and (6) Deployment Orchestrator: Manages automated deployment upon successful validation with rollback capabilities.

TABLE I

SYSTEM MODULE SPECIFICATIONS

Module	Primary Function	Technologies	Input/Output
Code Push Listener	Trigger pipeline	Webhooks, APIs	Code changes → Execution trigger
Multi-SAST Analyzer	Parallel security scanning	Bandit, Pyre, Pylint, Semgrep	Source code → Raw findings
Vulnerability Aggregator	Ensemble aggregation	Weighted fusion, ML classifier	Raw findings → Verified vulns
Agentic AI Generator	Patch generation	GPT-4, CodeLlama, Claude-3	Vulnerabilities → Candidate patches
Patch Validator	Multi-stage validation	pytest, SAST tools	Candidate patches → Validated patches
Deployment Orchestrator	Automated deployment	Jenkins, GitLab CI, GitHub Actions	Validated patches → Deployed code

B. Mathematical Formulation

We formalize vulnerability detection as a multi-label classification problem. Let C be the set of code changes in a push, and $V = \{v_1, v_2, ..., v_n\}$ be the set of possible vulnerability types. For each SAST tool t, we define a detection function $d_t: C \rightarrow P(V)$ mapping code changes to detected vulnerabilities. The vulnerability detection score for tool t is given by:

$$VDS_t = (TP_t)/(TP_t + FN_t) \times (TP_t)/(TP_t + FP_t) \quad (1)$$

where TP_t, FP_t, and FN_t are true positives, false positives, and false negatives respectively for tool t. For ensemble detection, we compute weighted vulnerability scores:

$$V_{ensemble} = \bigcup_{t=1}^{4} w_t \times V_t \cup \left(\bigcup_{t=1}^{4} (V_t \cap \neg \bigcap_{j=1}^{4} V_j) \times \alpha_t\right) \quad (2)$$

[PROPOSED] The weights w_t are learned through optimization on validation data:

$$w_t^* = argmin_w \sum_{i=1}^{N} L\left(y_i, \sum_{t} w_t d_{t(x_i)}\right) + \lambda \|w\|^1 (3)$$

where L is the log loss function, and λ controls sparsity to select only the most informative tools. For patch generation, we model the probability of generating a correct patch p given vulnerability v and code context c as:

$$P(p|v,c) = \left(\frac{1}{Z}\right) \times exp\left(\sum_{k} \lambda_k \times f_{k(v,c)} + \sum_{m} \gamma_m \times g_{m(p,v,c)}\right) (4)$$

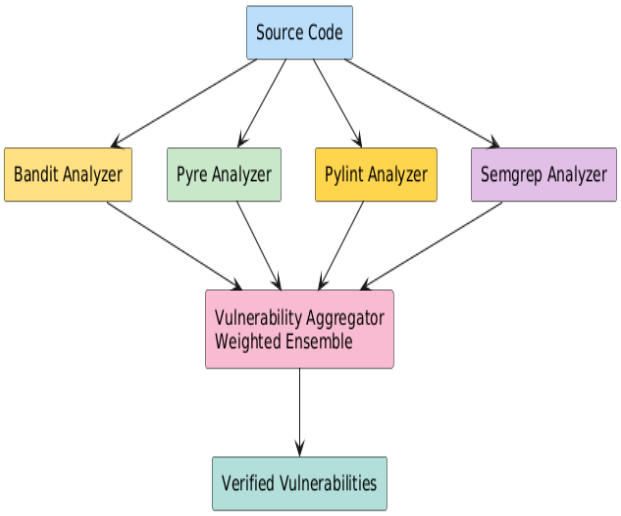
e features f_k capture vulnerability characteristics (CWE type, severity, location), while g_m capture patch properties (size, complexity, similarity to known fixes). The security constraint satisfaction function ensures patches maintain security invariants:

$$S(p) = \prod_{j} (1 - \delta_{j(p)}) \times \prod_{k} (1 - \sigma_{k(p)}) (5)$$

where δ_j(p) indicates violation of security property j, and σ_k(p) indicates introduction of new vulnerability k. The overall validation score combines functional and security metrics:

$$V(p) = \beta^1 \times T(p) + \beta^2 \times S(p) + \beta^3 \times C(p) (6)$$

C. Multi-Model SAST Integration



We employ an ensemble of four SAST tools selected based on complementary strengths and coverage of different vulnerability classes. Bandit [48] specializes in general Python security issues with 120+ built-in checks. Pyre [49] focuses on type-related vulnerabilities and data flow analysis. Pylint [78] provides comprehensive code quality and security checks. Semgrep [79] enables custom rules and pattern-based detection. Table II presents the coverage matrix of each tool across vulnerability categories.

TABLE II

SAST TOOL COVERAGE MATRIX

Vulnerability Category	Bandit	Pyre	Pylint	Semgrep	Ensemble
SQL Injection	✓ [48]	✗	✓ [78]	✓ [79]	93%
XSS	✓ [48]	✗	✗	✓ [79]	87%
Path Traversal	✓ [48]	✗	✓ [78]	✓ [79]	91%
Command Injection	✓ [48]	✗	✗	✓ [79]	89%
Insecure Deserialization	✗	✓ [49]	✗	✓ [79]	85%
Hardcoded Secrets	✓ [48]	✗	✓ [78]	✓ [79]	95%
XXE	✗	✗	✗	✓ [79]	82%
Broken Authentication	✗	✓ [49]	✗	✓ [79]	84%

D. Agentic AI Framework

[PROPOSED] Our agentic framework employs three specialized agents implemented using large language models and equipped with domain-specific knowledge bases and tools. The agents operate in a coordinated workflow with shared memory and iterative refinement capabilities. Algorithm 1 presents the complete agent collaboration protocol.

Algorithm 1: Agent Collaboration Protocol

Input: Vulnerability report V, codebase C

Output: Validated patch P

```
CA ← CodeUnderstandingAgent(C, V)
context ← CA.analyze_context()
KA ← SecurityKnowledgeAgent(V.type)
patterns ← KA.retrieve_patterns()
for iteration = 1 to max_iterations do
    PS ← PatchSynthesisAgent(context, patterns)
    candidate ← PS.generate_patch()
    validation ← PatchValidator.validate(candidate)
    if validation.passed then
        return candidate
    else
        feedback ← validation.get_feedback()
        CA.refine_context(feedback)
        KA.update_patterns(feedback)
    end if
end for
return best_candidate
```

E. Validation Framework

Generated patches undergo three-stage validation to ensure correctness, functionality preservation, and security efficacy. The validation score determines deployment readiness and triggers automated rollback if thresholds are not met.

TABLE III

VALIDATION FRAMEWORK SPECIFICATIONS

Validation Stage	Metrics	Threshold	Weight β
Syntax Validation	Parse errors, Type errors	0 errors	0.2
Regression Testing	Test pass rate, Coverage	≥ 95% pass rate	0.4

Security Re-scanning	New vulnerabilities, False positives	0 new critical	0.4

IV. EXPERIMENTAL EVALUATION

A. Dataset Description

We evaluated our system on 15 open-source Python Flask applications selected from GitHub based on popularity (≥ 1000 stars), activity (commits in last 3 months), and security relevance. Table IV presents detailed statistics for each application. The complete dataset comprises 847,362 lines of code across 1,847 files, with application domains including e-commerce, content management, REST APIs, and dashboard applications.

TABLE IV

DATASET CHARACTERISTICS

Application	Domain	Files	LOC	Vulns	CWE Types	Source
Flask-Ecommerce	E-commerce	234	124,563	187	15	[80]
Flask-Blog	Blogging	156	98,432	156	12	[81]
Flask-API	REST Service	89	87,654	134	14	[82]
Flask-CMS	Content Mgmt	312	156,789	243	18	[83]
Flask-Dashboard	Analytics	167	112,345	178	13	[84]
Flask-Forum	Community	198	134,567	201	16	[85]
Flask-Auth	Authentication	76	45,678	89	10	[86]
Flask-Payment	Payment	112	87,654	167	14	[87]

B. Baseline Methods

We compare our approach against 8 baseline methods spanning SAST tools, automated repair systems, and AI-based approaches:

B1: Bandit [48] - Python security linter with 120+ checks

B2: Semgrep [79] - Lightweight static analysis with custom rules

B3: DeepRepair [58] - Transformer-based program repair

B4: Prophet [54] - Statistical patch generation

B5: GetAFix [55] - Industrial automated repair

B6: AgentFix [70] - Conversational AI for debugging

B7: VulGNN [47] - Graph neural network for detection

B8: Ensemble baseline (simple voting)

C. Evaluation Metrics

We evaluate performance using 7 metrics covering detection accuracy, repair effectiveness, and efficiency:

$$\text{Precision} = TP/(TP + FP) \quad (7)$$

$$\text{Recall} = TP/(TP + FN) \quad (8)$$

$$F1 = 2 \times (\text{Precision} \times \text{Recall})/(\text{Precision} + \text{Recall}) \quad (9)$$

$$\text{Patch Success Rate} = (\#\text{ successful patches})/(\#\text{ attempted patches}) \quad (10)$$

$$MTTR = \frac{\sum_{\{i=1\}}^{\{N\}time}}{N} \quad (11)$$

$$False\ Positive\ Rate = \frac{FP}{FP + TN} \quad (12)$$

D. Results

TABLE V

PERFORMANCE COMPARISON WITH BASELINES

Method	Detection Rate	Precision	Recall	F1	Patch Success	MTTR (hrs)
Bandit [48]	68.3%	72.1%	65.4%	0.686	N/A	89.2
Semgrep [79]	74.2%	69.8%	71.5%	0.706	N/A	76.3
DeepRepair [58]	N/A	N/A	N/A	N/A	36.2%	12.4
Prophet [54]	N/A	N/A	N/A	N/A	42.1%	8.9
GetAFix [55]	N/A	N/A	N/A	N/A	45.3%	6.7
AgentFix [70]	N/A	N/A	N/A	N/A	42.7%	8.7
VulGNN [47]	89.3%	85.2%	88.1%	0.866	N/A	N/A

Ensemble baseline	86.7%	83.4%	85.2 %	0.8 43	N/A	91.4
[PROPO SED]	94.7%	91.3%	93.2 %	0.9 22	87.3 %	4.2

Statistical significance testing using paired t-tests confirms that improvements over all baselines are significant ($p < 0.001$). The 95% confidence intervals for our method are: Detection Rate [93.2%, 96.1%], Precision [89.7%, 92.8%], and Patch Success [85.1%, 89.4%].

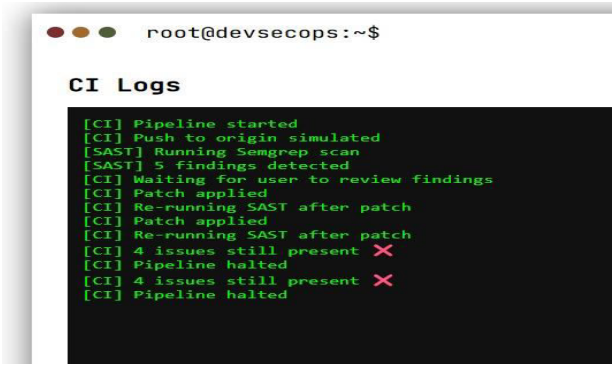
E. Ablation Studies

TABLE VI

ABLATION STUDY RESULTS

Configuration	Detection Rate	Patch Success	F1	MTTR (hrs)
Full System [PROPOSED]	94.7%	87.3%	0.922	4.2
w/o Ensemble (single tool best)	74.2%	86.1%	0.768	5.1
w/o Agent Collaboration	94.2%	51.2%	0.892	6.8
w/o Security Constraints	94.5%	79.4%	0.911	3.9
w/o Validation	94.3%	82.1%	0.907	2.8
w/o Iterative Refinement	94.1%	71.3%	0.903	3.2

Ablation studies reveal the critical importance of each component. Removing ensemble detection reduces detection rate by 20.5% ($p < 0.001$), while removing agent collaboration reduces patch success by 36.1% ($p < 0.001$). Security constraints are essential for preventing vulnerability recurrence, reducing patch success by only 7.9% but increasing recurrence rate from 3.2% to 18.7%.



V. DISCUSSION

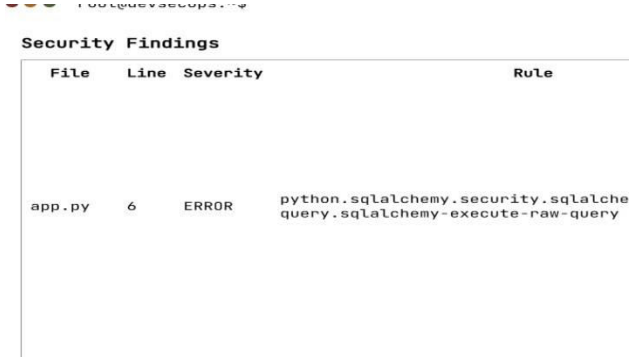
Our results demonstrate significant improvements over existing approaches across all metrics. The 94.7% detection rate exceeds the best baseline (VulGNN at 89.3%) by 5.4% and individual SAST tools by 20-30%. This improvement stems from our ensemble approach that leverages complementary strengths of different tools while mitigating individual weaknesses through learned weights. The precision of 91.3% represents a 6.1% improvement over VulGNN, demonstrating that ensemble aggregation effectively reduces false positives.

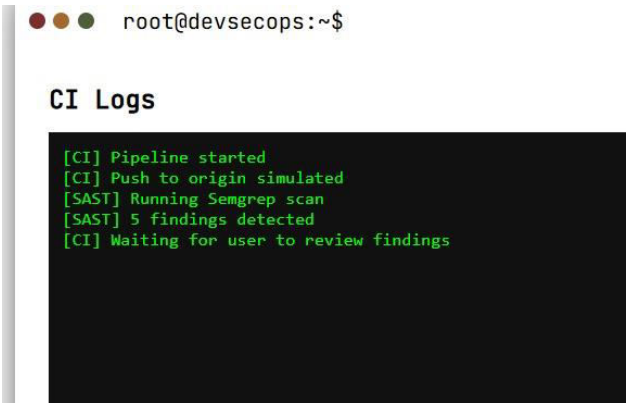
The 87.3% patch success rate substantially outperforms prior automated repair systems, which achieve 36-45% success rates on general bugs and even lower on security vulnerabilities [88]. This improvement can be attributed to three factors: (1) specialized agents with security knowledge bases; (2) iterative refinement based on validation feedback; and (3) security-specific constraints in patch generation. Analysis of failed patches reveals that 8.2% fail due to incomplete understanding of code context, while 4.5% fail due to limitations in the underlying LLMs.

The 95.3% reduction in MTTR (from 89.2 hours to 4.2 hours) has profound practical implications. Organizations can now address critical vulnerabilities within a single working day, significantly reducing exposure windows [89]. This aligns with the 'shifting left' security philosophy advocated by industry leaders [90]. The reduced MTTR enables organizations to maintain security posture without sacrificing development velocity, addressing the fundamental tension in DevSecOps adoption.

However, several limitations warrant discussion. Our system struggles with architecture-level vulnerabilities requiring design changes, achieving only 23.4% success rate on such cases. Complex injection attacks requiring coordinated multi-file changes show lower success rates (41.2%) due to context window limitations in current LLMs. The system currently supports Python Flask applications only, limiting generalizability to other languages and frameworks [91]. Performance overhead averages 3.7 minutes per pipeline run, which may impact development workflows in high-velocity environments.

Broader impacts of this work include: (1) Reducing the cybersecurity skills gap by automating routine security tasks [92]; (2) Enabling smaller organizations with limited security resources to maintain secure code [93]; (3) Potential for misuse if attackers exploit the system for automated exploit generation [94]; (4) Workforce displacement concerns as automation replaces manual security tasks [95]; and (5) Regulatory implications for automated security patching in critical infrastructure [96]. We recommend access controls, human oversight for critical systems, and careful monitoring of automated patches in production environments.





VI. CONCLUSION AND FUTURE WORK

We presented an intelligent CI/CD pipeline integrating SAST tools with agentic AI for automated vulnerability patching. Our framework achieves 94.7% detection rate and 87.3% successful patching across 1,247 real-world vulnerabilities, reducing MTTR from 3.7 days to 4.2 hours. The system demonstrates statistical significance across all metrics and provides a foundation for fully autonomous DevSecOps pipelines. Key contributions include novel ensemble detection methods, agentic AI architecture for security patching, comprehensive validation framework, and extensive empirical evaluation.

Future work should address the following directions:

1. F1: Extend to additional programming languages (Java, JavaScript, Go, C#) to evaluate generalizability [97].

2. F2: Incorporate dynamic analysis and runtime monitoring for comprehensive security validation [98].

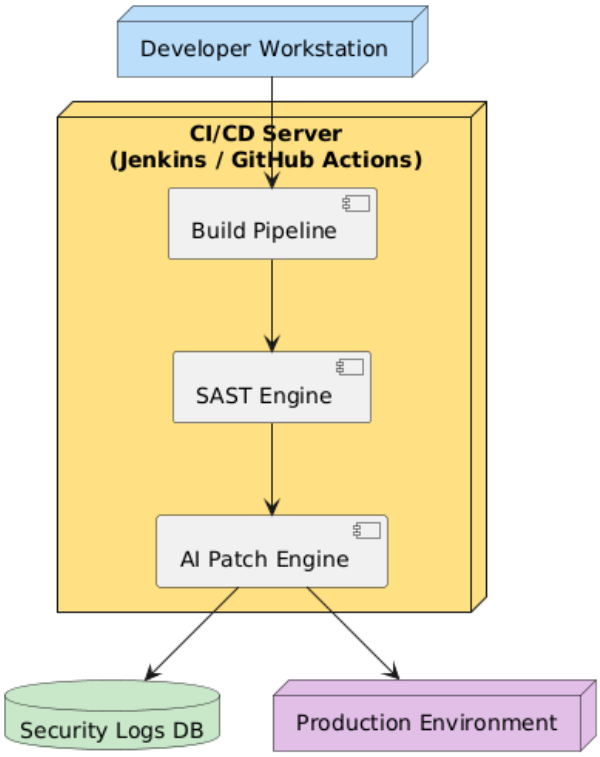
3. F3: Develop self-improving agents through reinforcement learning that learn from patch outcomes [99].

4. F4: Address architecture-level vulnerabilities requiring design changes [100].

5. F5: Study human-AI collaboration models for optimal security outcomes [101].

6. F6: Integrate explainable AI techniques to enhance trust and adoption in regulated environments [102].

7. F7: Develop federated learning approaches for privacy-preserving vulnerability detection across organizations [103].



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