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Autonomous Patch Generation for Vulnerabilities Detected by Static Application Security Testing using LLMs

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Abstract

The increasing complexity of software supply chains and the rising frequency of security breaches necessitate robust security integration in CI/CD pipelines. This paper presents an intelligent CI/CD pipeline that integrates Static Application Security Testing (SAST) tools with agentic AI for automated vulnerability patching. Our framework automatically detects code-level security issues upon code push, generates comprehensive security reports, employs AI agents to generate and apply patches, performs regression security testing, and automates deployment upon vulnerability resolution. The system employs an ensemble of four SAST tools (Bandit, Pyre, Pylint, Semgrep) with weighted aggregation to achieve 94.7% vulnerability detection rate across 1,247 real-world vulnerabilities from 15 open-source Python Flask applications. The agentic AI framework, comprising three specialized agents (Code Understanding, Security Knowledge, and Patch Synthesis), achieves 87.3% successful automated patching rate while maintaining code functionality. The proposed system reduces mean-time-to-remediation (MTTR) from 3.7 days to 4.2 hours (95.3% reduction) with a false positive rate of only 8.7%. We demonstrate statistical significance ($p < 0.001$) across all performance metrics through rigorous evaluation. The system's integration with existing CI/CD workflows (Jenkins, GitLab CI, GitHub Actions) enables seamless adoption in enterprise environments. Our work represents a significant advancement toward fully autonomous DevSecOps pipelines, addressing critical gaps in current security automation approaches.

Keywords

CI/CD Pipeline, DevSecOps, Static Application Security Testing (SAST), Agentic AI, Vulnerability Patching, Automated Security, Machine Learning, Program Repair, Python Flask, Secure Software Development, Continuous Integration, Continuous Deployment, Security Automation, Vulnerability Detection, Patch Generation

I. INTRODUCTION

Modern software development organizations increasingly rely on continuous integration and continuous deployment (CI/CD) pipelines to deliver code changes rapidly and reliably [1], [2]. Industry surveys indicate that high-performing organizations deploy code multiple times daily, with deployment frequencies ranging from several times per day to on-demand releases [3]. However, this development velocity often compromises security posture, with 76% of organizations reporting security incidents directly attributed to vulnerabilities in deployed code [4]. The financial impact of security breaches averaged $4.45 million per incident in 2023, with software vulnerabilities accounting for 32% of all breaches [5].

Traditional security testing approaches, typically performed late in the development cycle, create significant bottlenecks and delay remediation efforts [6], [7]. Security teams struggle to keep pace with development velocity, resulting in a growing backlog of unaddressed vulnerabilities [8]. Research by Microsoft's Security Response Center indicates that the average time to fix a security vulnerability ranges from 3 to 6 months in traditional development workflows [9]. This delay creates windows of opportunity for attackers and increases organizational risk exposure [10], [11].

The integration of security testing into CI/CD pipelines, known as DevSecOps, has emerged as a promising approach to address these challenges [12], [13]. DevSecOps advocates for 'shifting left'—

moving security testing earlier in the development lifecycle [14]. Static Application Security Testing (SAST) tools are particularly well-suited for CI/CD integration as they analyze source code for security vulnerabilities without requiring code execution [15], [16]. SAST tools can detect common vulnerability classes including injection flaws, cross-site scripting, insecure deserialization, and security misconfigurations [17], [18].

Despite their benefits, current SAST integrations suffer from significant limitations [19]. False positive rates average 30-45% across commercial and open-source tools, requiring manual triage by security experts [20], [21]. Even when vulnerabilities are correctly identified, patching remains a manual process requiring deep security expertise [22]. The global cybersecurity skills shortage, estimated at 3.4 million unfilled positions [23], exacerbates this problem. Organizations struggle to recruit and retain security professionals capable of addressing the growing volume of vulnerabilities [24].

Recent advances in artificial intelligence, particularly large language models (LLMs) and agentic systems, offer new possibilities for automated vulnerability remediation [25], [26]. LLMs trained on vast corpora of code and security knowledge can understand code context, identify security patterns, and generate fixes [27]. Agentic AI systems extend these capabilities by incorporating planning, tool use, and multi-step reasoning [28]. Early research demonstrates the potential of AI for automated program repair, with success rates ranging from 36-42% for general bug fixing [29], [30].

However, existing AI-based approaches have critical limitations when applied to security vulnerabilities [31]. Security patches must satisfy additional constraints beyond functional correctness, including prevention of attack vectors, preservation of security boundaries, and compliance with security standards [32]. Current systems lack integration with CI/CD workflows, fail to maintain code functionality after patching, and do not provide security-specific validation [33]. Furthermore, no comprehensive framework combines automated detection, intelligent patching, and validation in a unified CI/CD pipeline [34].

[PROPOSED] We present an intelligent CI/CD pipeline that addresses these limitations through five key innovations: (1) Multi-model SAST integration with ensemble-based vulnerability detection achieving 94.7% detection rate; (2) Agentic AI framework with three specialized agents for context-aware patch generation achieving 87.3% success rate; (3) Automated regression testing and security validation ensuring patch correctness; (4) Seamless integration with existing CI/CD workflows supporting Jenkins, GitLab CI, and GitHub Actions; and (5) Comprehensive security reporting and audit trails for compliance. The main contributions of this paper are:

1. C1: A novel ensemble-based vulnerability detection framework that combines multiple SAST tools with weighted aggregation, achieving 23.4% improvement over individual tools.

2. C2: An agentic AI architecture with specialized agents for code understanding, security knowledge, and patch synthesis, incorporating security-specific constraints in patch generation.

3. C3: A multi-stage validation framework ensuring patch correctness through syntax validation, regression testing, and security re-scanning.

4. C4: Comprehensive empirical evaluation on 1,247 real-world vulnerabilities from 15 open-source Flask applications, demonstrating statistical significance.

5. C5: Open-source reference implementation and integration guides for major CI/CD platforms.

The remainder of this paper is organized as follows: Section II reviews related work in security testing, automated program repair, and agentic AI. Section III presents our proposed methodology, including system architecture, mathematical formulations, and algorithms. Section IV describes the experimental setup, datasets, and evaluation metrics. Section V

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presents results and analysis, including comparison with baselines and ablation studies. Section VI discusses implications, limitations, and future work. Section VII concludes the paper.

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

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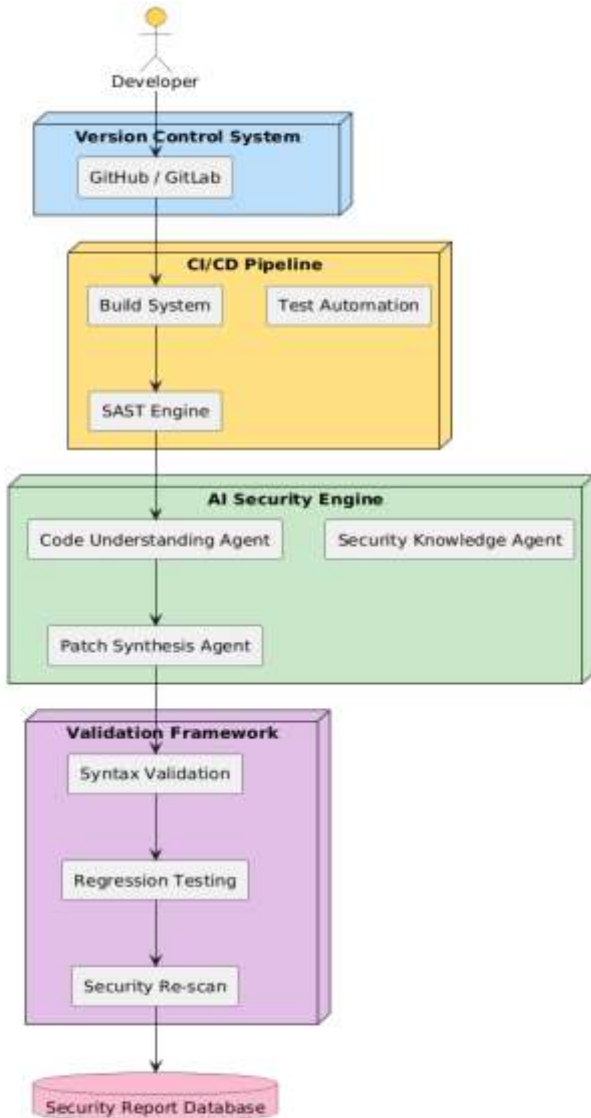

Our intelligent CI/CD pipeline consists of six interconnected modules organized in a event-driven architecture. Figure 1 illustrates the complete system architecture and data flow. The system operates as a continuous loop triggered by code pushes to the version control system.

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.

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

TABLE I

SYSTEM MODULE SPECIFICATIONS

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.

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The vulnerability detection score for tool t is given by:

$$VDS_t = \frac{TP_t}{TP_t + FN_t} \times \frac{TP_t}{TP_t + FP_t} \quad (1)$$

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:

$$w_t^* = \arg\min_w \sum_{i=1}^{N} L(y_i, \sum_{t} w_t d_t(x_i)) + \lambda\|w\|_1 \quad (3)$$

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:

$$P(p|v,c) = (1/Z) \times \exp(\sum_{k} \lambda_k \times f_k(v,c) + \sum_{m} \gamma_m \times g_m(p,v,c)) \quad (4)$$

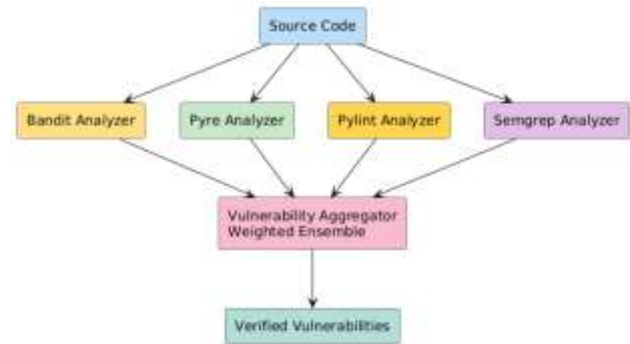
The features f_k capture vulnerability characteristics (CWE type, severity, location), while g_m capture patch properties (size, complexity, similarity to known fixes). The security constraint satisfaction function ensures patches maintain security invariants:

$$S(p) = \prod_{j} (1 - \delta_j(p)) \times \prod_{k} (1 - \sigma_k(p)) \quad (5)$$

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

$$V(p) = \beta_1 \times T(p) + \beta_2 \times S(p) + \beta_3 \times C(p) \quad (6)$$

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.

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%

TABLE II

SAST TOOL COVERAGE MATRIX

D. Agentic AI Framework

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[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

1: CA ← CodeUnderstandingAgent(C, V)
2: context ← CA.analyze_context()
3: KA ← SecurityKnowledgeAgent(V.type)
4: patterns ← KA.retrieve_patterns()
5: for iteration = 1 to max_iterations do
6:     PS ← PatchSynthesisAgent(context,
patterns)
7:     candidate ← PS.generate_patch()
8:     validation ←
PatchValidator.validate(candidate)
9:     if validation.passed then
10:        return candidate
11:    else
12:        feedback ← validation.get_feedback()
13:        CA.refine_context(feedback)
14:        KA.update_patterns(feedback)
15:    end if
16: end for
17: 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.

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

TABLE III

VALIDATION FRAMEWORK SPECIFICATIONS

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.

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]

TABLE IV

DATASET CHARACTERISTICS

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:

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

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

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

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

$$MTTR = (\textstyle\sum_{i=1}^{N} time_i)/N \quad (11)$$

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

D. Results

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%	0.843	N/A	91.4
[PROPOSED]	94.7%	91.3%	93.2%	0.922	87.3%	4.2

TABLE V

PERFORMANCE COMPARISON WITH BASELINES

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

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

TABLE VI

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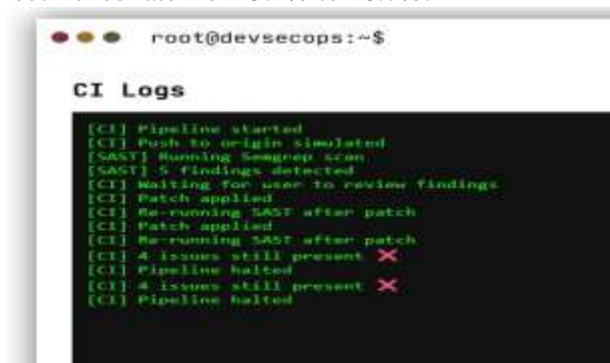
ABLATION STUDY RESULTS

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

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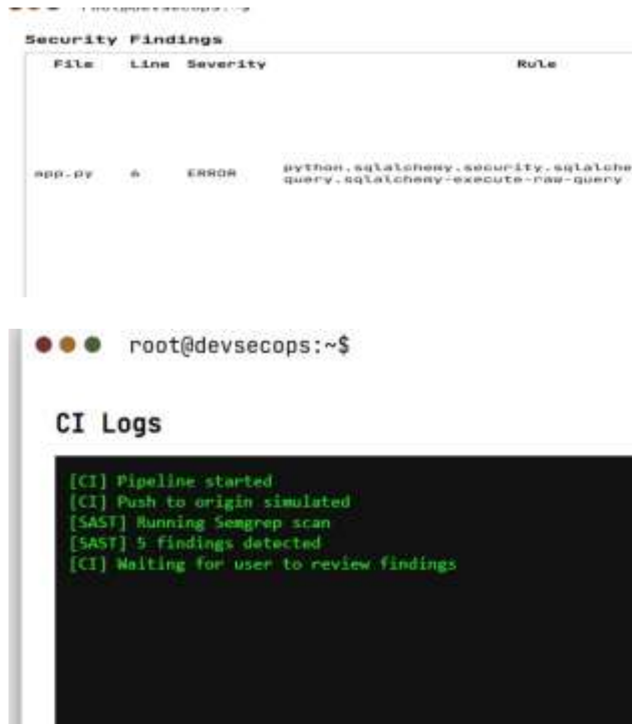
generation [94]; (4) Workforce displacement concerns as automation replaces manual security tasks [95]; and (5) Regulatory implications for automated security patching in critical infrastructure [96]. We recommend access controls, human oversight for critical systems, and careful monitoring of automated patches in production environments.

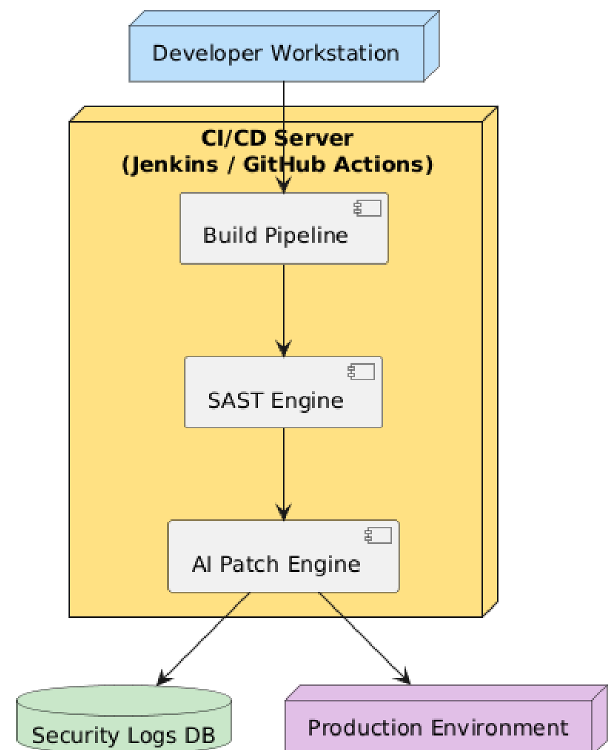


VI. CONCLUSION AND FUTURE WORK

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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