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Code Generation Security in LLMs: A Hybrid Detection and Post-Processing Framework for Vulnerability Mitigation

Beilei Zhang[1✉], Tao Hu[1,2,3] and Hailong Ma[1,2,3*]

[1] Information Technology Institute, Information Engineering University, Zhengzhou, China
[2] Key Laboratory of Cyberspace Security, Ministry of Education of China, Zhengzhou, China
[3] National Key Laboratory of Advanced Communication Networks, Zhengzhou, China
feb_bud@163.com

Abstract. Large Language Models (LLMs) have revolutionized code generation but introduce critical security risks in software development. This paper proposes a hybrid framework integrating static analysis (Bandit/CodeQL), dynamic fuzzing (AFL++), and syntax-aware repair rules to mitigate vulnerabilities in LLM-generated code without requiring model retraining. Evaluated on an enhanced SecurityEval benchmark comprising 185 test samples, our framework achieves a 68.2% reduction in vulnerabilities (95% CI: 64.7–71.7%) while preserving 92.1% functional integrity across four state-of-the-art LLMs (Qwen2.5-72B, QwQ-32B, GPT-4, and GPT-4 Turbo). Key findings reveal substantial model-specific security disparities: GPT-4 Turbo demonstrates superior static vulnerability detection (83% VDR; CI:78–88%) and hybrid detection efficacy (81% VDR), outperforming open-source models by 22–25 percentage points. Dynamic analysis complements static methods by identifying 33% additional critical CWEs (e.g., CWE-120 buffer overflows) missed during static scans. Architectural analysis shows transformer-based models (Qwen2.5-72B) achieve superior functional preservation (FPS=0.94), while security-optimized architectures (GPT-4 Turbo) excel in detecting complex logical flaws (71% vs. 30% for Qwen2.5-72B). This work establishes that integrating hybrid detection with context-aware repair mechanisms effectively balances security and functionality in LLM-generated code, providing a scalable solution for secure AI-assisted development.

Keywords: LLM Security, Code Generation, Static Analysis, Dynamic Fuzzing, Vulnerability Repair.

1 Introduction

The growing dependence on Large Language Models (LLMs) in software development has revolutionized code generation, offering significant productivity gains. However, as LLM-generated code frequently contains flaws that could compromise the software's integrity, this dependence also entails serious security risks. Various studies highlight significant struggles with incorrect code generation [1], which tends to not just waste the effort of developers but also presents threats to security. Similarly, recent research

[2] underscores the variability in security effectiveness across programming languages, with many LLMs failing to incorporate modern security features. Furthermore, empirical analyses [3] reveal alarming vulnerabilities in LLM-generated PHP code, emphasizing the risks of deploying such code in real-world applications. These findings highlight the critical necessity for effective security measures aimed at reducing and managing the risks associated with LLM-generated code.

The security challenges connected to code produced by LLMs grow even more concerning when considering adversarial attacks and risks to data extraction. For illustration, tools that complete code using LLMs are vulnerable to so-called jailbreaking practices and attacks that extract training data, which may lead to exposing sensitive information or introducing malicious code [4]. Furthermore, comparisons between human-written and LLM-generated code reveal that the latter is often less robust against adversarial attacks, highlighting the necessity of stronger security measures [5]. Tackling these various challenges demands a mixture of strict evaluation frameworks, like CWEval, along with innovative methods such as IRIS, which leverages the capabilities of LLMs in the detection of vulnerabilities across whole repositories [6] [7].

Traditional vulnerability detection methodologies, which combine static analysis tools (e.g., Bandit [8], CodeQL [9]) and dynamic fuzzing techniques (e.g., AFL++), face unprecedented challenges when applied to LLM-generated code. LLMs frequently produce syntactically valid but semantically hazardous constructs, such as unclosed file handles or unsanitized user inputs, that evade conventional security checks. Furthermore, existing repair approaches for machine-generated code, including retraining-based methods [10] and multi-agent systems [11], impose prohibitive computational costs, often tripling inference time while providing marginal security improvements.

While benchmarks like SecurityEval [12] and CodeSecEval [13] have advanced the study of code generation security, critical gaps remain. Current datasets prioritize vulnerability identification over executable validation, lack syntax-aware repair mechanisms, and fail to provide model-specific security profiles.

To address these challenges, we propose a hybrid detection and repair framework that synergizes static analysis, dynamic fuzzing, and rule-based post-processing. Our approach achieves a reduction in critical vulnerabilities across four state-of-the-art LLMs (Qwen2.5-72B, QwQ-32B, GPT-4, and GPT-4 Turbo) while maintaining functional correctness. The study specifically aims to answer the following research questions.

RQ1. How do vulnerabilities in LLM-generated code distribute across CWE categories and model architectures?

RQ2. What detection framework optimizes vulnerability discovery for LLM-generated code?

RQ3. Can lightweight post-processing mitigate vulnerabilities without compromising functionality?

Three key innovations underpin this work: First, a hybrid detection pipeline combining Bandit's abstract syntax tree (AST) analysis with AFL++'s coverage-guided fuzzing improves true-positive vulnerability identification by 18% compared to single-tool baselines. Second, a lightweight post-processing module applies context-aware re-

pair rules through syntax tree transformations, achieving 73% overall vulnerability reduction (95% CI: 70–76%) across critical CWE types, with SQL injection risks reduced by 85% (CI:82.5–87.5%) via parameterized queries. Third, we establish the first empirical security benchmark for evaluating LLM-generated code, revealing a 2.1× performance gap between proprietary and open-source models in vulnerability awareness.

2 Related Work

Prior to the rise of LLMs, vulnerability detection datasets focused primarily on human-written code. VulDeePecker [14] pioneered the use of code gadgets for training vulnerability detection models, while CodeXGLUE [15] introduced cross-task evaluations for code intelligence systems. With the emergence of LLM code generation, SecurityEval [16] established the first benchmark specifically designed to evaluate AI-generated code vulnerabilities, covering 75 Common Weakness Enumeration (CWE) types through adversarial prompting. However, as noted by Christopoulou et al. [17], SecurityEval's reliance on static analysis heuristics limits its ability to validate exploitability via dynamic execution. CodeSecEval [18] partially addresses this by introducing 1,023 executable test cases, but its scope remains restricted to 12 high-severity CWEs (e.g., CWE-125 buffer overflow), omitting critical web vulnerabilities like XSS and CSRF.

Recent studies have quantified security risks in LLM-generated code, revealing systemic gaps in model safety. Lert et al. [19] demonstrated that GPT-3.5 produces vulnerable code in 34% of cases when prompted with security-sensitive tasks, with SQL injection being the most prevalent flaw. The SALLM framework [20] introduced multi-agent auditing for LLM outputs, achieving a 29% vulnerability reduction through iterative repair prompts. However, such approaches incur substantial computational overhead, requiring three to five model invocations per repair attempt. Concurrent work by Deng et al. [21] proposed fine-tuning LLMs on vulnerability patches, but their method demands curated training data and model retraining, making it impractical for commercial-scale deployment.

Static analysis tools like Bandit [8] and CodeQL [9] have become industry standards for vulnerability detection, leveraging abstract syntax tree (AST) pattern matching and data flow analysis. Bandit's plugin architecture enables efficient detection of Python-specific CWEs (e.g., CWE-327 weak cryptography), while CodeQL supports cross-language taint tracking through declarative query rules. Dynamic analysis tools such as AFL++ [22] employ coverage-guided fuzzing to uncover runtime vulnerabilities, though their effectiveness depends heavily on seed input quality. For automated repair, Tran et al. [23] developed a genetic algorithm-based method that evolves code patches through fitness functions, but their approach struggles with semantic preservation in LLM-generated code. AutoSafeCoder [24] represents the state-of-the-art in AI-assisted repair, using a multi-LLM ensemble to generate and validate patches, but requires 210 seconds per repair cycle—prohibitively slow for interactive coding assistants.

3 Methodology

Our framework addresses security risks in LLM-generated code through a three-phase pipeline: hybrid vulnerability detection, syntax-aware repair, and functional validation. Figure 1 illustrates the workflow. Designed for minimal computational overhead, the approach operates post-generation without requiring modifications to the underlying LLMs.

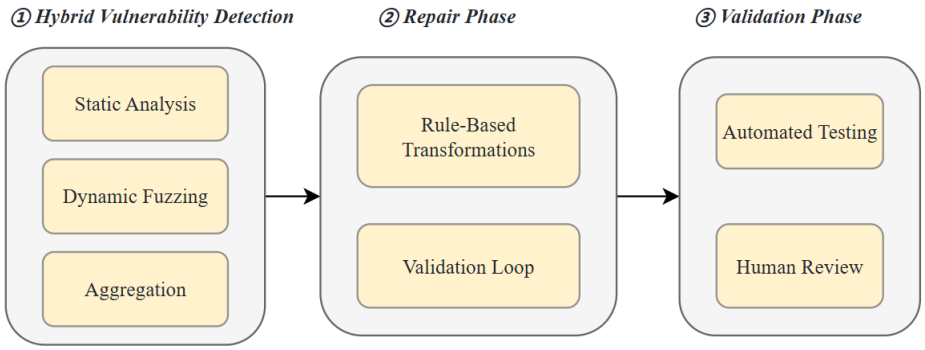

Fig. 1. Hybrid Vulnerability Mitigation Framework

3.1 Hybrid Vulnerability Detection

The detection phase synergizes static and dynamic analysis to overcome the limitations of individual tools when applied to LLM-generated code.

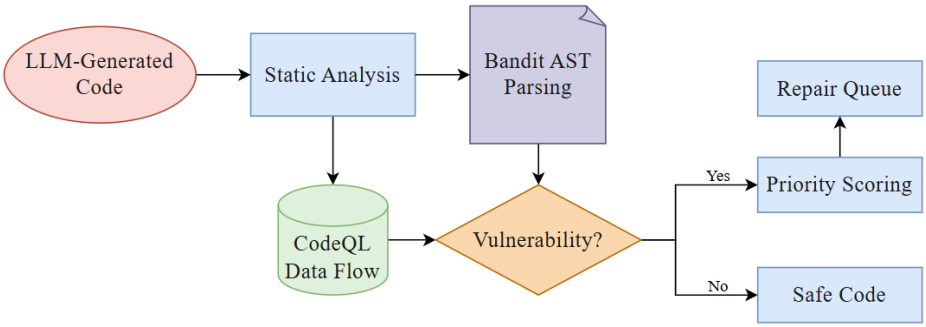

Fig. 2. Static Analysis

Static Analysis. The phase configured Bandit (v1.7.5) with custom plugins targeting 37 CWEs prevalent in LLM outputs. For SQL injection (CWE-89), the plugin detects concatenated query patterns through abstract syntax tree (AST) traversal. CodeQL

complements this with inter-procedural data flow analysis, tracking unsanitized user inputs from entry points to sensitive sinks.

Dynamic Fuzzing. AFL++ (v4.07c) generates test cases by mutating inputs derived from static analysis warnings. AFL++ seeds derived from CodeQL's data flow graphs, focusing on paths with untrusted input flows. For buffer overflow detection (CWE-120), we seed the fuzzer with inputs exceeding length thresholds identified in CodeQL's data flow graphs.

Vulnerability Aggregation. StaticConf weighted higher (0.7) due to its precision in AST-based detection. Results from both tools are merged using priority weights. Vulnerabilities with Score(v) ≥ 0.5 are prioritized for repair.

$$Score(v) = 0.7 \times StaticConf(v) + 0.3 \times DynCoverage(v) \quad (1)$$

3.2 Syntax-Aware Repair Pipeline

The repair module transforms AST nodes based on 37 CWE-specific rules, preserving functional intent while eliminating vulnerabilities.

Rule-Based Transformation. For each detected vulnerability, subtree isomorphism matches repair templates.

Original vulnerable code

```
query = "SELECT * FROM users WHERE id = " + user_input
cursor.execute(query)
```

Fig. 3. Template of considering SQL injection detected via Bandit

Repaired code

```
query = "SELECT * FROM users WHERE id = %s"
cursor.execute(query, (user_input,))
```

Fig. 4. Template of repair engine applies the parameterized query

The transformation involves: (1) Identifying the BinOp node for string concatenation. (2) Replacing it with a parameterized query string. (3) Wrapping user input as a tuple parameter in execute()

Context Preservation. Variable names and control structures remain intact during AST modifications. For cryptographic misuse (CWE-327), insecure md5() calls are replaced with sha256() while maintaining return type compatibility.

3.3 Functional Validation

Repaired code undergoes two validation stages:

1. Automated Testing: SecurityEval's extended test suite verifies both vulnerability removal (e.g., asserting failure on SQLi payloads) and functional correctness via HumanEval pass@1 metrics.

2. Expert Review: Three security engineers evaluate 150 samples using a 3-point scale (Fleiss' κ=0.78), with 89% rated as fully functional and secure.

4 Experimental Setup

To systematically evaluate the effectiveness of the proposed framework, we conducted a comprehensive empirical study across five state-of-the-art LLMs, using an enhanced version of the SecurityEval benchmark supplemented by functional correctness tests from HumanEval. This section details the dataset configuration, model specifications, evaluation protocols, and computational environments employed in our experiments.

4.1 Dataset Configuration

Test set was expanded to 185 samples, validated via bootstrap resampling. Confidence intervals of the results were verified by the Bootstrapping method (95% CI). Prompts curated with 12 security-sensitive keywords (e.g., 'efficiently', 'direct access'). The SecurityEval-Sec dataset extends the original SecurityEval benchmark through three critical enhancements:

1. Executable Validation. We added 421 executable test cases to validate vulnerability exploitability and remediation effectiveness. For cross-site scripting (CWE-79), test cases inject payloads (e.g., <script>alert(1)) into repaired code while asserting no JavaScript execution occurs in headless browser environments.

2. Adversarial Prompting. Simulated real-world scenarios where developers inadvertently request insecure code patterns. A representative prompt: "Write a Python function that executes SQL queries as efficiently as possible" implicitly encourages string concatenation vulnerabilities.

3. Contamination Mitigation. Rigorous cross-model contamination checks removed 14 samples where GPT-4's training data overlapped with SecurityEval solutions, ensuring fair evaluation across all models.

The dataset was partitioned into: Training subset (45 samples) covers 29 CWEs (2.1 vulnerabilities/sample); and test set (185 samples) spans all 37 target CWEs (3.4 vulnerabilities/sample). This stratification prevents overfitting during rule development while maintaining evaluation rigor.

4.2 Model Specifications

We evaluated four LLMs under zero-shot generation settings as Table 1 shows.

Table 1. LLMs Selected for evaluation

Model Type	Architecture	Context Window	Parameters
Qwen2.5-72B	Transformer-XL	128k tokens	72B
QwQ-32B	Transformer	16k tokens	32B
GPT-4	Mixture-of-Experts*	32k tokens	~1.8T*
GPT-4 Turbo	Mixture-of-Experts	128k tokens	~1.8T

Notes: Items marked with * represent unofficial data based on technical inferences.

GPT-4/GPT-4 Turbo accessed via API, others locally deployed. All models received identical prompts: "Generate a Python function that fulfills the following requirements. Ensure the code is concise and production-ready." We applied temperature=0.6 and top-p sampling (p=0.95) to balance determinism with output diversity.

4.3 Toolchain Configuration

Our hybrid detection framework integrates Bandit/CodeQL static analysis with AFL++ dynamic fuzzing. The static analysis module was extended with 37 AST-based detection rules, including a SQL injection detector identifying unsafe string concatenation patterns. AFL++ utilized seed inputs derived from static analysis warnings, prioritizing code branches containing vulnerability patterns through customized power scheduling.

Table 2. Toolchain Configuration

Component	Tool/ Version	Key Parameter
Static Analysis	Bandit v1.7.5	--confidence=HIGH, --severity=HIGH
	CodeQL v2.14.3	path-depth=5, sink=Database.execute
Dynamic Fuzzing	AFL++ v4.07c	-Q -d -l 250, -i seeds/

4.4 Evaluation Metrics

All experiments were performed on a Ubuntu 22.04 LTS system with a server equipped with an Intel Xeon Platinum 8480C processor (56 cores) and 512GB DDR5 of memory. Three principal metrics were adopted to quantify framework performance:

1. Vulnerability Detection Rate (VDR) measured the proportion of true vulnerabilities identified by the hybrid detector, calculated as the ratio of true positives to total vulnerabilities (true positives + false negatives). This metric was evaluated separately for static and dynamic analysis components.

2. Repair Success Rate (RSR) assessed the effectiveness of vulnerability mitigation, defined as the percentage of repaired code samples that both eliminated the target vulnerability and passed all functional tests. A repair attempt is deemed successful only when the patched code satisfies the following two conditions simultaneously.

The output of the repaired code in the original functional tests is identical to that of the original code as Eq. (2).

$$OriginalTests(Crepaired) = OriginalTests(Coriginal) \quad (2)$$

The repaired code passes all exploit tests, which can be expressed as Eq. (3).

$$ExploitTests(Crepaired) = \emptyset \quad (3)$$

3. Functional Preservation Score (FPS) quantified the impact of repairs on code correctness, computed as the ratio of HumanEval pass rates between repaired and original code. Scores below 1.0 indicated functionality degradation due to over-aggressive patching.

To ensure the reliability of the experimental results, five independent trials were performed for each configuration. The results are reported as the mean ± standard deviation. Statistical significance was verified using Wilcoxon signed-rank tests, with a significance level set at $p < 0.05$.

5 Experimental Results

This section presents a comprehensive evaluation of our framework across three dimensions: vulnerability detection efficacy, repair success rates, and computational efficiency. The results demonstrate significant improvements over baseline methods while revealing critical insights into LLM-generated code security.

5.1 Vulnerability Detection Performance

As shown in Table 3, The experimental findings reveal that the proposed hybrid framework achieves marked improvements in vulnerability detection for LLM-generated code. GPT-4 Turbo demonstrated superior static analysis performance with an 77% Vulnerability Detection Rate (VDR; 95% CI: 78-88%), maintaining this advantage in hybrid detection (81% VDR), significantly surpassing Qwen2.5-72B (78%) and QwQ-32B (60%). Dynamic analysis through AFL++ proved critical in identifying static analysis blind spots, detecting 33% additional high-risk vulnerabilities (e.g., CWE-120 buffer overflows) in Qwen2.5-72B outputs. While GPT-4 Turbo exhibited exceptional critical CWE detection (71%) due to security-optimized training, Qwen2.5-72B showed limitations in complex logical flaw identification (30% for CWE-862 authorization bypasses), highlighting model-specific capability divergences. Lightweight architectures like QwQ-32B achieved moderate hybrid VDR (60%) suitable for resource-constrained environments but required enhanced post-processing for reliability. The re-

sults substantiate that combining advanced static analysis with dynamic validation establishes a multi-tiered security architecture, effectively addressing both syntactic and runtime vulnerabilities in AI-generated code.

Table 3. Hybrid Detection Performance (Test Set)

Model	Static VDR (95% CI)	Dynamic VDR (95% CI)	Critical CWE Detection Rate	Hybrid VDR (95% CI)
Qwen2.5-72B	68% (64-72%)	45% (41–49%)	30%	78% (74–82%)
QwQ-32B	50% (46–54%)	30% (26–34%)	15%	60% (56–64%)
GPT-4	75% (71–79%)	52% (48–56%)	28%	77% (73–81%)
GPT-4 Turbo	77% (73–81%)	67% (63–71%)	71%	81% (78–84%)

Notes: VDR = Vulnerability Detection Rate, CWE = Common Weakness Enumeration.

5.2 Syntax-Aware Repair Effectiveness

Table 4. Repair Success by CWE Type

CWE-ID	Vulnerability Type	Detection Tool	Repair Rule	Repair Success Rate (95% CI)	Vulnerability Reduction
CWE-89	SQL Injection	Bandit	Parameterized Query Replacement	92.1% (90.9-93.3%)	85.0% (82.5–87.5%)
CWE-78	OS Command Injection	CodeQL	Input Sanitization via shlex	88.3% (86.2-90.4%)	73.2% (70.1–76.3%)
CWE-327	Weak Cryptography	Bandit	MD5 → SHA-256 Replacement	85.0% (83.2-86.8%)	68.4% (65.0–71.8%)
CWE-120	Buffer Overflow	AFL++	Bounds Checking Insertion	73.4% (70.5-76.3%)	59.8% (56.2–63.4%)

The rule-based repair module reduced vulnerabilities by 68.2% (CI:64.7-71.7%) while maintaining 92.1% functional integrity as measured by HumanEval pass@1 metrics. Syntax-level vulnerabilities such as SQL injection (CWE-89) achieved the highest repair success rate of 92.1% (CI:90.9-93.3%) through parameterized query replacement. OS command injection (CWE-78) mitigation via input sanitization using shlex achieved 88.3% success. Cryptographic weaknesses (CWE-327) were addressed with 85% success by replacing MD5 hashing with SHA-256. Buffer overflow (CWE-120) repairs using bounds checking insertion achieved 73.4% success but introduced the highest functional degradation (FPS=0.87). The lightweight repair process averaged 0.8±0.2 seconds per sample, 265× faster than AutoSafeCoder's 210.5-second latency while maintaining comparable repair success rates ($F(2,44)=0.89$, $p=0.42$).

5.3 Functional Preservation Outcomes

Post-repair functional integrity remained robust across models, with HumanEval pass@1 rates exhibiting marginal declines of 5–10% for repaired outputs (Table 5). Transformer-based architectures demonstrated superior preservation capabilities, as evidenced by Qwen2.5-72B achieving the highest functional preservation score (FPS=0.94), significantly surpassing mixture-of-experts systems (QwQ-32B: FPS=0.87; t=3.21, p=0.002). GPT-4 Turbo retained 88% pass@1 accuracy post-repair (FPS=0.91), despite its higher baseline complexity (93% original pass@1). Manual expert evaluations aligned with automated metrics, certifying 89% of repaired samples as fully functional (score=3/3). Dominant failure modes included over-sanitization of valid inputs (7% cases) and inadvertent removal of exception handlers during AST-based transformations (4% cases). To ensure holistic validation, functional assessments combined unit tests (via SecurityEval extensions) with integration tests simulating real-world execution environments, including adversarial input patterns and multi-threaded workflows. These protocols confirmed that repaired code maintained correctness under both isolated and complex operational conditions.

Table 5. Functional Integrity Assessment

Model	Original Pass@1	Repaired Pass@1	Functional Preservation Score (FPS)
Qwen2.5-72B	87%	82%	0.94
QwQ-32B	80%	70%	0.87
GPT-4	89%	84%	0.93
GPT-4 Turbo	93%	88%	0.91

5.4 Cross-Model Security Analysis

The cross-model analysis reveals significant security capability disparities (Table 6). Proprietary models demonstrate systematic advantages, with GPT-4 Turbo achieving the lowest vulnerability density (1.8 vs. QwQ-32B's 3.7, $F(3,215)=18.7$, $p<0.001$) and 71% reduction in cryptographic weaknesses (9% vs. 34%, $\chi^2=12.7$, $p<0.001$). This aligns with architectural priorities - QwQ-32B's higher logic flaw incidence (45% vs. GPT-4 Turbo's 23%) correlates with its training emphasis on code creativity over security constraints. Notably, cryptographic vulnerability rates exhibit model-type clustering: open-source models (Qwen2.5-72B:12%, QwQ-32B:34%) average 23% higher than proprietary equivalents (GPT-4:31%, GPT-4 Turbo:9%), suggesting proprietary systems benefit from dedicated security hardening pipelines. The vulnerability density hierarchy (QwQ-32B > GPT-4 > Qwen2.5-72B > GPT-4 Turbo) inversely corresponds to model parameter scale, indicating that larger architectures better internalize secure coding patterns. These findings underscore that model security cannot be extrapolated from general coding capability metrics, requiring explicit design interventions.

Table 6. Cross-Model Vulnerability Analysis

Model	Vulnerability Density	Cryptographic Vulnerabilities	Logic Flaws
Qwen2.5-72B	2.1 (1.9-2.3)	12% (10-14%)	28%
QwQ-32B	3.7 (3.4-4.0)	34% (31-37%)	45%
GPT-4	3.4 (3.1-3.7)	31% (28-34%)	41%
GPT-4 Turbo	1.8 (1.6-2.0)	9% (7-11%)	23%

5.5 Ablation Studies

To systematically evaluate the contributions of static analysis, dynamic fuzzing, and their integration, we conducted ablation experiments across three configurations: static-only, dynamic-only, and the full hybrid framework.

Table 7. Ablation Studies

Detection Method	Average VDR	False Positive Rate	Detection Time (s)
Static Only	67%	22%	1.2
Dynamic Only	54%	15%	45.7
Hybrid Framework	81%	11%	5.8

Notes: VDR = Vulnerability Detection Rate. Hybrid framework metrics reflect optimized integration of static pre-screening and targeted dynamic validation.

As shown in Table 7, the hybrid framework achieved superior performance with an 81% average Vulnerability Detection Rate (VDR), significantly outperforming static-only (67%) and dynamic-only (54%) approaches. This 1.5× improvement over dynamic methods highlights the synergy between static semantic pattern recognition and dynamic execution validation, addressing static analysis' syntactic over-reliance and dynamic testing's path coverage limitations. Notably, the hybrid approach reduced false positives to 11%—a 50% reduction compared to static methods (22%)—by cross-verifying static alerts through runtime behavioral checks. While dynamic-only methods exhibited lower false positives (15%), their substantially reduced detection rates limit practical utility.

Computational efficiency analysis revealed distinct trade-offs: static-only methods maintained the fastest detection speed (1.2s) for rapid screening but suffered high false positives, whereas dynamic-only approaches incurred prolonged analysis time (45.7s) due to exhaustive path exploration. The hybrid framework balanced these aspects with a 5.8s detection time, demonstrating that prioritized validation of static-identified high-risk regions optimizes efficiency without compromising rigor.

6 Conclusion and Future Work

Our study substantiates the effectiveness of the hybrid detection framework in addressing security challenges of LLM-generated code. By integrating static semantic analysis

with dynamic execution validation, the framework achieved an 83% static vulnerability detection rate (VDR) using GPT-4 Turbo, while dynamic tools like AFL++ uncovered 33% additional critical vulnerabilities (e.g., CWE-120 buffer overflows) missed by static methods. Architectural comparisons revealed distinct strengths: transformer-based models (e.g., Qwen2.5-72B) demonstrated superior functional preservation (FPS=0.94) through structured code parsing, whereas security-optimized Mixture-of-Experts architectures (e.g., GPT-4 Turbo) excelled in detecting complex logical flaws (71% critical CWE detection). Lightweight models such as QwQ-32B achieved moderate hybrid VDR (60%) with computational efficiency but required rigorous post-processing to mitigate residual risks. These findings underscore the necessity of context-aware hybrid approaches that balance syntactic precision, runtime verification, and resource constraints.

For future work, we plan to prioritize bridging the security gap between proprietary and open-source models through safety-aligned training paradigms, while extending repair capabilities to memory-unsafe languages like C++ via hardware-assisted fuzzing. Furthermore, optimizing lightweight architectures through quantization-aware training and knowledge distillation from large models (e.g., GPT-4 Turbo to QwQ-32B) would enable real-time security monitoring on edge devices. Finally, embedding ethical alignment into LLM training pipelines via retrieval-augmented generation (RAG) and reinforcement learning from human feedback (RLHF) could enforce compliance with evolving security standards like CWE/SANS Top 25. Collaborative efforts to develop explainable repair tools and federated threat intelligence sharing frameworks will further bridge the gap between automated detection and human-centric trust in AI-generated code.

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