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Adaptive Self-Healing Software Systems Using Large Language Models:Bridging Configuration Validation, Vulnerability Detection, and Specification Learning

Somasekhar Gubbala

Principal Systems Architect - Distributed systems, Metaforge IT Solutions ,Inc, USA

Abstract

Software reliability is a persistent challenge due to dynamic misconfigurations, hidden vulnerabilities, and evolving system specifications. Although recent advances in Large Language Models (LLMs) have shown great potential in various software engineering tasks—such as configuration validation, vulnerability detection, and specification generation—each of these works tends to focus on isolated aspects of reliability.

In this paper, we present AutoHeal, a novel LLM-driven framework for adaptive self-healing software systems that unifies these capabilities. AutoHeal employs multi-phase reasoning:

(1) validating configurations using prompt-conditioned analysis,

(2) detecting vulnerabilities through contextual code exploration, and

(3) reconstructing specifications to maintain system consistency.

We introduce an LLM-ensemble learning approach that adaptively tunes prompts and responses based on system feedback and historical corrective actions. Experimental results on ten open-source projects demonstrate that AutoHeal achieves an average precision improvement of 18% over state-of-the-art single-task baselines in identifying and automatically remediating misconfigurations and vulnerabilities.

This work opens a new direction in building resilient and intelligent self-managed software systems powered by large-scale language models.

Introduction

Software failures frequently stem from misconfigurations, latent vulnerabilities, and incomplete specifications, leading to significant operational disruptions and financial losses. Traditional tools for identifying and mitigating these issues rely heavily on manually crafted rules or system-specific machine learning models that demand extensive field data, making them neither scalable nor adaptive to new system environments.

With the advent of Large Language Models (LLMs) such as GPT-4, CodeLlama, and Gemini, the paradigm of software engineering has shifted dramatically. LLMs demonstrate exceptional capacity for few-shot learning, contextual reasoning, and code understanding, enabling automation in tasks such as bug detection, code generation, and specification derivation.

However, while individual research directions—such as LLM-based configuration validation (e.g., Ciri), LLM-assisted vulnerability detection, and LLM-generated software specifications—have shown promising results, they remain largely isolated. There exists no unified system that integrates these strengths into an adaptive, self-healing framework capable of dynamic error detection, reasoning, and remediation [1–3].

Modern software systems rely heavily on configurable parameters, evolving codebases, and continuously updated documentation. While this flexibility enhances adaptability, it also introduces significant reliability and security challenges. Misconfigurations remain one of the leading causes of system outages and performance degradation. Similarly, undetected vulnerabilities in source code can lead to severe security breaches. In addition, inconsistencies between documentation, implementation, and runtime behavior often result in specification drift and unintended system behavior.

Traditional approaches to configuration validation, vulnerability detection, and specification extraction largely depend on handcrafted rules, static analysis tools, or supervised machine learning models trained on system-specific datasets. These methods are often expensive, difficult to generalize across systems, and limited in adaptability.

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***Corresponding Author:** Somasekhar Gubbala, Principal System Architect-Distributed systems, Metaforge IT Solutions ,Inc, USA; E-mail: sekharsomapega82@gmail.com

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Recent advances in Large Language Models (LLMs) [4,5] have demonstrated remarkable capabilities in understanding natural language, source code, and structured data. Their few-shot learning ability allows them to perform complex reasoning tasks without extensive retraining. Consequently, LLMs have been explored for configuration validation, vulnerability detection, specification generation, and code synthesis.

However, existing research typically addresses these problems in isolation. There is a lack of an integrated framework that synergistically combines configuration reasoning, code-level vulnerability analysis, and formal specification regeneration within a unified adaptive feedback cycle.

This limitation motivates the development of the AutoHeal framework, which leverages LLMs in a coordinated manner to enable resilient, self-adaptive software systems.

This paper proposes Auto Heal, an LLM-based, self-healing frame work that unifies multiple software assurance tasks underonecognitivelayer. The keycontributions are: A multi-modal LLM prompt orchestration mechanism for integrating validation, detection, and specification. Anadaptive feedback-guided tuning process that refines

prompts based on real system responses. An empirical evaluation demonstrating the unified framework's performance across diverse open-source projects.

Basic Concepts

Large Language Models in Software Engineering

LLMs are deep neural networks trained on massive text and code corpora to under-stand, generate, and reason over both natural and programming languages [6–12]. In software engineering, LLMs have been applied for:

Codegeneration (translatingnatural-language descriptions in to code)Vulnerabil-ity detection (identifying insecure code patterns) Specification generation (inferring functional requirements) Configuration validation (checking correctness of configura-tion parameters)

Self-Healing Software

Self-healing software refers to systems that can autonomously detect, diagnose, and repair faults with minimal human intervention. Traditional self-healing relies onpattern-based models or rules. AutoHeal introduces the first LLM-based cognitiverepair system, enabling contextual reasoning-driven healing.

Literature Survey

This section reviews prior work in applying Large Language Models to software engineering tasks relevant to the AutoHeal framework.

Large Language Models a sConfiguration Validators

Mis configurations are a major source of software failures. Traditional validation tech-niques rely on manually written rules or large-scale field data to train machine learning models, which are costly and system-specific [13].

The Ciri framework presents the first comprehensive study evaluating LLMs for configurationvalidation.Ciriemploysprom ptengineeringwithfew-shotlearningusing both valid and invalid configuration examples. To address hallucination and non de-terminism issues, it incorporates output checking mechanisms. The framework was evaluated across eight LLMs and ten widely deployed open-source systems.

The results demonstrate that LLMs show strong potential for configuration validation. However, challenges remain, including difficulty detecting certain mis-configuration types and bias toward popular configuration parameters. Importantly, Ciri focuses solely on configuration correctness and does not integrate vulnerability detection or runtime adaptation mechanisms.

Large Language Models for Vulnerability Detection

Prior vulnerability detection approaches relied on medium-sized pretrained models or smaller neural networks trained from scratch. The emergence of advanced LLMs such

as GPT-3.5 and GPT-4 has opened new possibilities due to their few-shot learning capabilities [14].

This study evaluates LLM effectiveness in vulnerability detection using prompt-based methods. Experimental results indicate that GPT-3.5 achieves competitive performance compared to prior state-of-the-art methods, while GPT-4 consistently outperforms them.

Despite promising results, these approaches primarily focus on source code anal-ysiswithoutincorporatingconfigurationcontext orspecification-levelreasoning.As aresult,theylackholisticsystem-levelawareness, which is critical for adaptive self-healing systems.

LLMs for Software Specification Generation

Software specifications play avital role inverification, testing,andbugdetec-tion. Existing techniques that convert natural language documentation into formal specifications often suffer from limited generalizability and high manual effort [15].

This work introduces the first open-sourced dataset (CEG) for event generalization and systematically evaluates zero-shot and few-shot performance of both open-source and closed-source LLMs. Results indicate that LLMs possess robust generalization capabilities, which improve with additional few-shot examples.

Although focused on NLP tasks, this research highlights LLM strengths in contextual reasoning and generalization—capabilities that are essential for linking configurationstates, code behavior, and run time events in adaptive software systems.

Research Gap and Motivation

The reviewed literature demonstrates that LLMs are effective in:

- Configurationvalidation
- Vulnerabilitydetection
- Specificationgeneration
- Codesynthesisandbenchmarking
- Contextualeventreasoning

However, these contributions operate independently. No existing framework inte-grates configuration validation, vulnerability detection, specification regeneration, and runtime feedback into a unified adaptive loop.

This integration gap motivates the AutoHeal framework,

which combines these capabilities into a continuous LLM-driven feedback cycle. By synergizing configu-ration, code, and specification understanding, AutoHeal aims to enable resilient, self-correcting software systems.

Proposed Idea: The Auto Heal Framework

Overview

Auto Heal is designed as an adaptive self-healingecosystem powered by multiple LLMs orchestrating three layers of reasoning. Configuration Analyzer: Detects and auto-corrects misconfigurations. Vulnerability Inspector: Identifies insecure coding patterns and suggests fixes. Specification Synthesizer :Regenerates and reconciles missingor inconsistent functional specifications. Together, these modules interact dynami-cally—validated configurations feed into secure coding analysis, whose outputs inform updated formal specifications.

Algorithmic Description

TheAutoHeal Adaptive Feedback Cycleis an iterative self-healing framework that integrates configuration validation, vulnerability detection, and specification rea-soning into a unified adaptive loop. The goal of the framework is to automatically detect, diagnose, and repair system faults while ensuring convergence toward a stable and resilient system state.

The algorithm takes as input a software repositoryR, configuration filesC, and runtime logs L, and produces an updated healed system state S The process executes iteratively until convergence criteria are satisfied.

Algorithm 1: AutoHeal Adaptive Feedback Cycle

Require: Software repository R, configurations C, runtime logs L

Ensure: Healed system state S'

1. Initialize convergence flag ← false
2. **while** not converged **do**

Phase 1: Configuration Validation

3. Apply LLM prompt P_1 trained on valid/invalid configuration pairs
4. Compute configuration validity score:
   $V_c \leftarrow f_{LLM_1}(C)$

Phase 2: Vulnerability Detection

5. **for all** code snippets $s_i \in R$ **do**
6. Apply LLM prompt P_2 to s_i
7. **end for**
8. Compute vulnerability assessment:
   $V_d \leftarrow f_{LLM_2}(R)$

Phase 3: Specification Regeneration

9. Generate specification:
   $S_f \leftarrow f_{LLM_3}(docs, R)$
10. Identify inconsistencies between S_f and runtime logs L

Phase 4: Feedback Optimization

11. Compute learning feedback:
    $F_{learn} \leftarrow \alpha(V_c, V_d, S_f)$
12. Update prompts and weighting parameters α based on prior errors

Phase 5: Healing Action Proposal

13. Generate candidate actions:
    $A \leftarrow \{$config fixes, code patches, specification updates$\}$
14. **if** Confidence(A) > θ **then**
15. Apply selected healing actions
16. Update system state S'
17. **end if**
18. Check convergence of F_{learn}
19. **end while**
20. **return** S' satisfying convergence criteria

Phase1: ConfigurationValidation

In the first phase, the system analyzes configuration parameters using a Large Lan-guage Model (LLM) guided by prompt P1, which is trained on examples of valid and invalid configurations. The model computes a configuration validity score:

$$V_c = f_{\mathrm{LLM}_1}(C)$$

This score estimates the likelihood of mis configurations or risky parameter settings.

Early detection of configuration faults helps prevent cascading failures.

Phase 2: VulnerabilityDetection

The second phase examines the source code repository R.Eachcodesnippetsi Ris analyzed using promptP2specialized for vulnerability detection. The aggregated vulnerability assessment is computed as:

$$V_d = f_{\mathrm{LLM}_2}(R)$$

This step identifies potential security weaknesses, unsafe coding practices, and logic flaws that may interact with configuration states.

Phase 3: Specification Regeneration

In this phase, the system synthesizes a formal specification from documentation and source code.

$$S_f = f_{\mathrm{LLM}_3}(\mathrm{docs}, R)$$

The regenerated specification Sfacts as a behavioral contract describing intended system behavior. The framework comparesSfwith runtime logsL to detect incon-sistencies between expected and observed behavior. This grounding step reduces hallucinations and stabilizes decision-making.

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Phase4: Feedback Optimization

The outputs of the previous phases are combined using an adaptive learning function:

$$F_{\text{learn}} = \alpha(V_c, V_d, S_f)$$

Here, α represents dynamically adjusted weighting parameters. Based on prior cycle errors, prompts and weights are updated to refine reasoning strategies. This adaptive mechanism improves stability and reduces false positives over successive iterations.

Phase 5: Healing Action Proposal

Using the integrated analysis, the system generates candidate healing actions:

A={config fixes, code patches, spec updates}

Each proposed action is evaluated through a confidence function. If:

Confidence(A)>θ

the selected healing actions are applied, producing an updated system state S'

Convergence Mechanism

After applying healing actions, the framework evaluates whether Flearnhas converged. Convergence indicates that validation scores and confidence levels have stabilized. If convergence is not achieved, the process repeats using refined prompts and updated system context.

Core Insight

The key contribution of AutoHeal is the integration of configuration reasoning, vulner-ability analysis, and specification regeneration within a continuous adaptive feedback loop. Ratherthan treating these tasks independently, the framework enablescross-phase interaction and runtime grounding. This synergy transforms static LLM-based analysis into a dynamic, self-correcting system capable of progressively improving reliability and resilience.

Running Example

1. Scenario: Consider an Apache server with a faulty configuration "KeepAliveTimeout 0" that causes repeated connection drops.

2. Configuration Analysis: The configuration analyzer flags "KeepAliveTimeout 0" as a low-validity parameter setting.

3. Vulnerability Inspection: The vulnerability inspector identifies insecure timeout handling logic in server.c.

4. Specification Regeneration: The specification synthesizer derives the corrected formal requirement:

"The server must maintain persistent connections with a default timeout ≥ 5 seconds."

5. Healing Action: AutoHeal updates the configuration to "KeepAliveTimeout 5".

6. Validation: The system verifies that the remediation restores

Table1 : Performance Comparison of Models

Model	P	R	F1	HSR
GPT-4	0.77	0.80	0.78	73%
CodeLlama	0.72	0.75	0.73	68%
Gemini2.0Pro	0.79	0.81	0.80	76%
AutoHeal	0.86	0.88	0.87	85%

Experimental Analysis

Dataset

To evaluate the effectiveness of the proposed Auto Heal framework, we curated adataset consisting of 10 widely deployed open-source systems, including Apache, MySQL, Redis, Nginx, and other production-grade infrastructure software. These projects were selected because they contain real-world mis configuration cases and documented vulnerability instances.

For each system, we collected:

- Histori calmis configuration reports,
- Vulnerability disclosures (e.g., improper validation, timeout handling, access control issues),
- Corresponding source code revisions,
- Configuration files and run time logs.

The dataset contains both isolated faults (configuration-only or code-only issues)and compound faults where mis configuration and code vulnerabilities interact. This enables evaluation of both independent and synergy is tic detection capabilities.

Compared Models

We compared the following models:

- GPT-4: Used with structured prompts for configuration validation and vulnerability detection.
- CodeLlama-70B: Applied in a few-shot setup for code-centric analysis.
- Gemini 2.0 Pro: Evaluated using prompt-based multi-task reasoning.
- AutoHeal Ensemble: Our proposed adaptive framework integrating configuration validation, vulnerability detection, and specification regeneration within a feedback loop.

All baseline models were evaluated independently without cross-phase feedback. In contrast, AutoHeal combines outputs across phases and iteratively refines prompts and weighting parameters.

Evaluation Metrics

We used standard classification and system-level metrics: Precision (P): Fraction of correctly identified healing actions among all proposed actions. Recall (R): Fraction of actual issues correctly identified. F1-score: Harmonic mean of precision and recall. Healing Success Rate (HSR): Percentage of healing actions that successfully restore system stability without introducing regressions.

While Precision and Recall measure detection quality, HSR evaluates real-world remediation effectiveness, which is critical for adaptive systems.

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Results and Discussion

The experimental results demonstrate that AutoHeal consistently outperforms standalone LLM models across all metrics.

Reduction of False Positives

The adaptive feedback cycle significantly reduces false positive healing actions. Stan-dalone models occasionally generate plausible but unnecessary configuration or code modificationsduetohallucinationorlimitedcontextualreasoning. Byincorporat-ing feedback from runtime logs and regenerated specifications, AutoHeal filters out low-confidence actions, resulting in higher precision and improved Healing Success Rate.

Stability Through Specification Regeneration

Specification regeneration plays a critical role in maintaining confidence stability across iterations. Without specification grounding, baseline models exhibit fluctuating outputs across repeated evaluations due to nondeterministic reasoning.

By synthesizing a formal specification and comparing it with runtime behavior, AutoHeal anchors decisions in structured constraints, reducing output variance and improving convergence behavior.

Synergistic Gains from Cross-Phase Integration

A key observation is that configuration validation and vulnerability detection complement each other. In several cases, vulnerabilities were triggered only under specific configuration settings. Standalone models analyzing code or configuration in isolation failed to capture such interactions.

The integrated framework enables cross-phase reasoning:

Configuration anomalies guide targeted vulnerability inspection. Vulnerability reports influence configuration re-evaluation. Specification regeneration reconciles both with expected runtime behavior.

This synergy leads to measurable gains in both Recall and F1-score compared to independent analysis.

Adaptive Convergence Behavior

AutoHeal's learning function dynamically adjusts prompt weights based on prior cycle errors. Empirically, we observed that the system converges within a small number of iterations (typically 2–4 cycles).

After convergence, healing actions stabilize and confidence scores remain consistently above the acceptance threshold.

Key Findings

- The adaptive feedback loop significantly improves precision by filtering hallucinated or low-impact fixes.
- Specification regeneration enhances robustness and reduces nondeterministic output behavior.
- Combining configuration and vulnerability reasoning yields synergistic improvements in detection and remediation.
- Healing Success Rate (HSR) better reflects practical system reliability than traditional classification metrics alone.

Overall, the results validate that integrating configuration validation, vulnerability detection, and specification synthesis within a unified adaptive loop provides substantial advantages over isolated LLM-based approaches.

Related Work

Existing research demonstrates that Large Language Models (LLMs) are highly effective when applied to individual software engineering tasks such as configuration validation, vulnerability detection, specification generation, and code synthesis.

However, these approaches operate largely in isolation. Configuration validation systems do not incorporate runtime behavior analysis; vulnerability detection models lack integration with configuration semantics; and specification generation frameworks are typically disconnected from dynamic system execution and adaptive feedback mechanisms.

Table 2: Summary of Related Workin LLM- Based Software Engineering

Work	FocusArea	LLMRole	Limitations
LLMsas Configura-tion Validators (Ciri)	Configuration correctness	Few-shotvalida-tionprompts	Limited parameter coverage
LLMs for Vulnerabil-ity Detection	Code security analysis	Prompt-based recognition	Weakc onfigcontext awareness
Generating Software Specifications	NL-to-formal spectrans forma-tion	Converts com-mentstoFOL	No run time integra-tion
Benchmarking LLMs for Code Generation	Text-to-codesyn-thesis	Evaluation framework	Focuson accuracy, notresilience
Event Generalization withLLMs	Event context reasoning	Few-shotgeneral-ization	No software-level linking

not connected to adaptive remediation; and benchmarking studies prioritize accuracy rather than system resilience.

Consequently, current solutions fail to provide a unified framework that syner-gizes configuration analysis, code inspection, and formal specification reasoning. This integration gap motivates the development of the AutoHeal framework, which com-bines these capabilities into a continuous adaptive feedback cycle for resilient software systems.

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