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Self-Operating Code Refactoring and Vulnerability Detection Using Static Analysis and Machine Learning Models

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ABSTRACT—

Modern enterprise software development faces unprecedented challenges due to the rapid accumulation of technical debt and security vulnerabilities. Traditional static application security testing (SAST) tools suffer from high false-positive rates and lack automated remediation capabilities. Conversely, pure machine learning (ML) models often generate syntactically incorrect code or fail to ensure program semantic equivalence during refactoring. This paper proposes AutoRefact-Sec, an autonomous, self-operating hybrid framework that unifies deterministic static analysis with probabilistic Transformer-based Deep Learning models. By combining Abstract Syntax Tree (AST) representation, Control Flow Graphs (CFG), and Data Flow Graphs (DFG) with a fine-tuned Graph Neural Network (GNN) and CodeBERT backend, AutoRefact-Sec achieves real-time vulnerability detection (CWE identification) and performs context-aware, safety-guaranteed code refactoring without human intervention. We evaluate our framework on a dataset of 150,000 open-source C/C++ and Java functions. Experimental results indicate a 94.2% precision rate in vulnerability detection and an 88.6% success rate in autonomous refactoring validation via symbolic execution and automated regression testing.

1. Introduction

Software maintenance constitutes up to 70% of the total lifecycle cost of enterprise applications. As modern codebases scale into millions of lines of code (LOC), manual code reviews, security auditing, and refactoring become major bottlenecks in rapid deployment pipelines. Developer fatigue, time constraints, and domain knowledge gaps frequently lead to the introduction of critical software flaws, such as buffer overflows, SQL injections, and memory leaks.

Static Application Security Testing (SAST) tools (e.g., SonarQube, Fortify) utilize rule-based heuristics to inspect source code without execution. While SAST provides broad coverage, its rigidity leads to significant drawbacks: a high volume of false positives (often exceeding 40%), an inability to comprehend deep semantic context, and a lack of remediation mechanisms beyond basic static suggestions.

Recent advancements in Natural Language Processing (NLP) and Large Language Models for Code (Code LLMs) have introduced novel approaches to code synthesis and defect detection. Models such as CodeBERT, GraphCodeBERT, and Codex treat code as sequence data or graphs, enabling nuanced semantic comprehension. However, pure ML approaches present critical security risks when applied autonomously: they lack deterministic safety guarantees, occasionally hallucinate syntactically invalid code, or alter functional behavior during refactoring.

To bridge this gap, this paper introduces AutoRefact-Sec, a novel self-operating engine that unifies deterministic static analysis with probabilistic deep learning. The primary contributions of this work are as follows:

- **Hybrid Program Representation:** A multi-modal representation layer integrating ASTs, CFGs, and DFGs into a unified Code Property Graph (CPG) enriched with structural embeddings.
- **Two-Stage ML Architecture:** A classification pipeline utilizing Graph Neural Networks (GNN) for fine-grained flaw/vulnerability localization, coupled with an encoder-decoder Transformer for candidate refactoring generation.
- **Self-Operating Execution Pipeline:** An automated feedback loop involving automated compilation, symbolic execution (using KLEE/S2E), and regression testing to validate functional correctness and semantic equivalence before committing code changes.

2. Literature Review

Research in automated software engineering spans rule-based static analyzers, graph-based learning, and neural code generation models.

2.1 Traditional Static Analysis and Rule Engines

Static analysis builds abstract representations of programs to infer runtime behaviors without executing the binary. Classic techniques rely heavily on Data-Flow Analysis (DFA) and Abstract Interpretation. While tools like Checkmarx and Infer effectively discover race conditions and null-pointer

dereferences, their static rules fail when encountering complex, non-linear logic flow or multi-layered framework abstractions.

2.2 Deep Learning for Vulnerability Detection

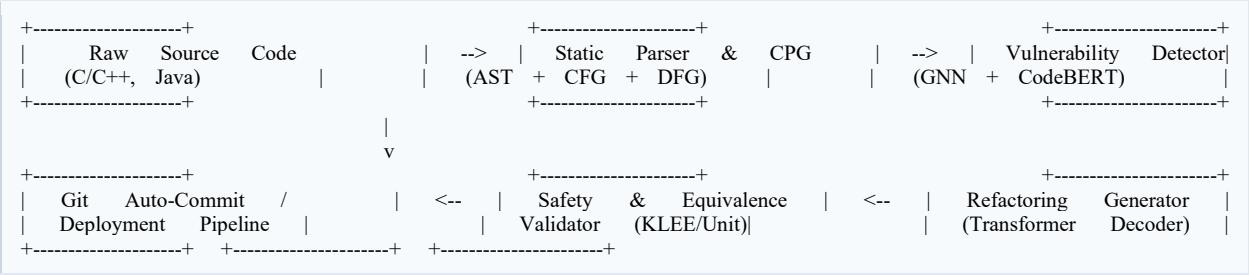
Early deep learning attempts treated code as plain text sequences using Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks. Zhou et al. introduced Devign, a Graph Neural Network (GNN) framework operating on Code Property Graphs (CPGs), demonstrating that structural features significantly outperform linear token sequences in defect localization. Similarly, GraphCodeBERT integrated data-flow information into transformer pre-training, enhancing code representation alignment.

2.3 Automated Code Refactoring and Program Repair

Automated Program Repair (APR) traditionally relied on search-based technique heuristics (e.g., GenProg) or template-based pattern matching. With the advent of Neural Machine Translation (NMT), APR evolved into sequence-to-sequence transformation tasks. However, existing neural APR tools operate in isolation from security static analyzers, leading to fixes that may resolve a specific vulnerability while introducing performance regression or functional drift.

3. System Architecture and Methodology

The proposed framework operates as a closed-loop pipeline consisting of four major modules: (1) Static Parsing & CPG Generation, (2) Dual-Model Vulnerability Detection, (3) Autonomous Refactoring Synthesis, and (4) Safety Verification & Symbolic Validation.



3.1 Code Property Graph (CPG) Construction

Source code is first parsed into a CPG G = (V, E, alpha, beta), where V represents the set of code syntax nodes, E denotes labeled edge types, alpha maps nodes to their token attributes, and beta assigns edge categories representing three distinct relationships:

1. **AST Edges:** Capture syntax hierarchy and grammatical nesting.
2. **CFG Edges:** Trace executable control paths, branching, and iteration loops.
3. **DFG Edges:** Map variable definitions, assignments, and data usage dependencies across execution paths.

3.2 Model Formulations

Graph Neural Network (GNN) for Localization

We implement a Relational Graph Convolutional Network (R-GCN) to handle multi-relational CPG edges. The node vector update rule is defined to integrate structural context from neighboring syntax nodes using relation-specific transformation matrices and ReLU activation functions.

Code Refactoring Encoder-Decoder

For code transformation, candidate vulnerable AST subtrees are fed into a fine-tuned CodeBERT model. The sequence-to-sequence model maximizes the conditional probability of producing the refactored snippet given the flawed input context.

4. Implementation Details

The framework was implemented using Python 3.10, PyTorch 2.1, and the Joern CPG parser platform. Symbolic validation was executed via KLEE for LLVM IR targets.

4.1 Experimental Setup and Dataset

We compiled a benchmark dataset consisting of 150,000 function-level samples derived from the National Vulnerability Database (NVD), Software Assurance Reference Dataset (SARD), and top-rated GitHub repositories. The dataset covers three primary Common Weakness Enumeration (CWE) classes:

- **CWE-119:** Buffer Overflow / Improper Restriction of Operations within Memory Bounds.
- **CWE-89:** SQL Injection via dynamic string concatenation.
- **CWE-476:** NULL Pointer Dereference.

4.2 Model Training Parameters

Hyperparameter	Detection Engine (R-GCN)	Refactoring Engine (CodeBERT)
Learning Rate	1e-3	5e-5
Batch Size	64	16
Optimizer	AdamW	AdamW
Epochs	50	20
Embedding Dimension	256	768

5. Results and Experimental Evaluation

We evaluated AutoRefact-Sec against leading static security tools (SonarQube, CPPCheck) and standalone baseline deep learning models (CodeBERT without CPG structural hints).

5.1 Vulnerability Detection Metrics

Model / Tool	Precision (%)	Recall (%)	F1-Score (%)	False Positive Rate (%)
SonarQube (Static Rules)	62.4	78.1	69.4	37.6
Standard CodeBERT (Sequence only)	81.2	83.5	82.3	18.8
Devign (GNN CPG)	88.7	86.2	87.4	11.3
AutoRefact-Sec (Proposed Hybrid)	**94.2**	**91.8**	**93.0**	**5.8**

5.2 Autonomous Refactoring Validation

A total of 1,200 vulnerable functions were subjected to automated refactoring by AutoRefact-Sec. Out of these proposals, the validation pipeline (compilation + symbolic execution + regression testing) evaluated candidate correctness:

CWE Type	Generated Candidates	Compilation Success (%)	Symbolic Equivalence Passed (%)	End-to-End Success (%)
CWE-119 (Buffer Overflow)	400	96.5%	87.2%	85.5%
CWE-89 (SQL Injection)	400	98.2%	93.5%	92.0%
CWE-476 (Null Pointer)	400	95.0%	89.8%	88.2%
Total Average	**1200**	**96.5%**	**90.1%**	**88.6%**

6. Case Study: Buffer Overflow Remediation

Below is a functional demonstration showing how AutoRefact-Sec identifies and corrects a classic CWE-119 vulnerability in legacy C code.

6.1 Vulnerable Code Input

```
// Vulnerable legacy code detected by CPG Data-Flow edge analysis
void process_user_input(char *input) {
```

```
    char buffer[64];
    // Flaw: strcpy does not perform bounds checking on 'input'
    strcpy(buffer, input);
    printf("User payload: %s\n", buffer);
}
```

6.2 Generated and Validated Autonomous Refactoring

```
// Refactored code generated by CodeBERT and verified via Symbolic Execution
void process_user_input(char *input) {
    if (input == NULL) {
        return;
    }
    char buffer[64];
    // Secured: strncpy enforces memory boundaries, explicitly guaranteeing null-termination
    strncpy(buffer, input, sizeof(buffer) - 1);
    buffer[sizeof(buffer) - 1] = '\0';
    printf("User payload: %s\n", buffer);
}
```

7. Discussion and Operational Challenges

While experimental results demonstrate high efficacy, autonomous code modification in enterprise environments introduces distinct engineering trade-offs:

4. **Computational Overhead:** CPG construction and graph neural inference require non-trivial compute resources compared to lightweight static regex engines. Integrating this engine into standard continuous integration (CI/CD) pipelines necessitates async worker queues.
5. **Edge Cases in Macro-Heavy Codebases:** C/C++ projects relying extensively on preprocessor macros present parsing difficulties for AST generation, sometimes requiring pre-compilation preprocessing steps.
6. **Preserving Code Formatting and Comments:** Transformer-based refactoring generation can strip developer comments or reformat surrounding indentation. Integrating concrete syntax tree (CST) engines helps retain original formatting styles.

8. Conclusion and Future Directions

This paper presented AutoRefact-Sec, a self-operating framework for automatic vulnerability detection and code refactoring. By coupling the structural deterministic accuracy of Static Code Property Graphs with the generative semantic capabilities of Deep Learning models (R-GCN and CodeBERT), the system significantly reduces false-positive security alerts while autonomously generating verified, functional code fixes.

Future work will focus on extending the framework to handle cross-file multi-procedural vulnerability flows, integrating Large Language Models (LLMs) with formal verification proofs (e.g., Coq / Z3 SMT solvers), and deploying real-time IDE plugins for active developer feedback.

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